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Accounting for Heterogeneity in Growth Incidence in Cameroon

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Abstract

This paper presents counterfactual decompositions based on both the Shapley method and a generalization of the Oaxaca-Blinder approach to identify proximate factors that might explain differences in the distribution of economic welfare in Cameroon in 1996–2007. In particular, the analysis uses re-centered influence function regressions to link the growth incidence curve for 2001–2007 to household characteristics and account for heterogeneity of impact across quantiles in terms of the composition (or endowment) effect and structural (or price) effect. The analysis finds that the level of the growth incidence curve is explained by the endowment effect while its shape is driven by the price effect. Observed gains at the bottom of the distribution are due to returns to endowments. The rest of the gains are accounted for by the composition effect. Further decomposition of these effects shows that the composition effect is determined mainly by household demographics while the structural effect is shaped by the sector of employment and geography. Finally, analysis of the rural-urban gap in living standards shows that, for the poorest households in both sectors, differences in household characteristics matter more than the returns to those characteristics. The opposite is true for better-off households.

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Accounting for Heterogeneity in Growth Incidence in Cameroon

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1. Introduction

For the past twenty years or so, Cameroon has been battling a severe and persistent socioeconomic crisis that can be traced back to a terms-of-trade shock in the mid 1980s and the associated policy response. Prior to that crisis, the country enjoyed steady economic growth and relative social stability. For about 20 years following independence in 1960, the average annual growth rate of Gross Domestic Product (GDP) hovered around 5 percent. That growth was driven mainly by the agricultural sector which employed more than 80 percent of the labor force and accounted for 32 percent of GDP. This sector was also a major contributor to export earnings through mainly cocoa and coffee (Benjamin and Devarajan 1986). The manufacturing sector accounted for about 25 percent of GDP and was mainly involved in import-substituting activities.

Cameroon became an oil producer in 1978 following the discovery of oil off the west coast of the country. This presented policymakers with a new set of opportunities and challenges. At that point in time, poor infrastructure and low levels of human capital were considered serious obstacles to development efforts. Some of the oil revenues could then be invested in capital formation. At the same time, there was a risk of Dutch disease[1] whereby traditional exports such as cocoa and coffee would lose competitiveness in the world markets as a result of domestic inflation induced by a rapid spending of oil revenues. In the early 1980s, the oil sector began to take over from the agricultural sector as the engine of growth. Between 1977 and 1981 the average rate of economic growth was about 14 percent and dropped to about 7.5 percent per year between 1982 and 1986 (Blandford et al. 1994). The share of the oil sector in GDP grew steadily from 1 percent in 1978 to 20 percent in 1985. During the same period the share of agriculture declined from about 29 percent to about 21 percent. Furthermore, the share of petroleum and oil products in exports increased from 3 percent to 65 percent while that of agricultural products plummeted from 87 percent to 27 percent.

The constant and steady growth achieved throughout the 1970s and 1980s earned Cameroon the title of middle-income country, a World Bank classification it shared with

[1] This term refers to the deterioration of the Netherlands' export competitiveness associated with the exploitation of natural gas fields in the 1970s (Benjamin and Devarajan 1985).

countries such as Indonesia, Morocco, Thailand and Tunisia. Cameroon's per capita GNP in 1988 dollars was estimated at US $1,010 (World Bank 1990). These positive achievements in economic growth were generally attributed to fiscal prudence and political stability. The World Development Report of 1988 did praise Cameroon along with Indonesia for managing cautiously the windfall from the 1979-1981 oil boom[2].

The fact that Cameroon did enjoy high and sustained economic growth throughout 1965-1985 has been abundantly documented (Bradford et al. 1994, World Bank 1995). However, little is known about trends in inequality and poverty during those "good" times for lack of data. Based on the 1983 Household Expenditure Survey, the World Bank (1995) found evidence of high levels of inequality in the distribution of income and rural poverty. The same report discusses factors indicating that the situation may not have been much better in years prior to the 1983 survey. While acknowledging that many urban residents did benefit from this growth episode, the report points to the following factors as contributing to high rural poverty: (1) an incentive structure that favored capital-intensive methods of production over labor-intensive ones; (2) an urban bias in the selection of public investment; and (3) the lack of human capital development in the rural areas.

In 1985, the economy was hit by a collapse of world prices of the country's major export commodities, namely oil, cocoa and coffee. This was further complicated by a 40 percent appreciation of the CFA franc between 1985 and 1988, and gains in competitiveness by Nigeria since 1985. The export price index fell by 65 percent for oil, 24 percent for cocoa, 11 percent for coffee and 20 percent for rubber (Bradford et al. 1994). Faced with this difficult international environment, the government adopted initially a strategy of internal adjustment[3] between 1985 and 1993. This entailed cutting back on public spending (mainly investment spending) and building up arrears. This policy choice was in part dictated by the fact that, as a member of the franc zone, Cameroon did not have the option of adjusting the nominal exchange rate to deal with the terms of trade shocks. Early 1989, Cameroon entered a structural adjustment supported

[2] It is reported that Cameroon saved up to 75 percent of the oil revenues abroad, and after the boom, ensured that expenditure grew slower than revenues in order to avoid deficits (World Bank 1988).

[3] This point in time also marks the abandonment of five-year plans for socioeconomic management. The last one was the 5th Five Year Development Plan covering the 1982-1986 period.

by the International Monetary Fund (IMF), the World Bank and the African Development Bank.

The crisis and the initial response to it led to a severe recession and increased poverty (World Bank 1995). It is reported that by 1990, real GDP stood 20 percent below its 1985 level. Furthermore, per capita income fell by about 50 percent between 1986 and 1993. The loss of competitiveness also led to the loss of export markets for agricultural products and made it hard for domestic food crops and industrial products to compete with imports. This squeeze implied a decrease of demand for labor both for tradable and non-tradable goods with adverse effects on living standards for both rural and urban areas. Also, reduced economic activity combined with a slackening of tax collection crippled the ability of the state to provide services, thus worsening the impoverishment.

In 1994, the Central African Economic and Monetary Community[4] of which Cameroon is a member devalued the CFA franc by about 50 percent in nominal terms (30 percent real), and implemented additional trade and fiscal reforms. This presented Cameroon with an opportunity to reverse the socioeconomic downturn. The country did experience some positive growth after the devaluation, but it was only in mid 1996, after some failed stabilization and adjustment efforts, that the government showed strong commitment to meaningful policy reforms. The successful implementation of these reforms led to macroeconomic stability and an average growth rate of real GDP in the neighborhood of 5 percent between 1997 and 2000. On the basis of the 1996 and 2001 household surveys, it is estimated that the incidence of poverty fell by 13 percentage points from about 53 percent to about 40 percent. However, income inequality remained high with the Gini index of inequality decreasing only by 3 percentage points, from 44 to 41 percent. Furthermore, other social indicators have not shown such an improvement.

A shift in borrowing strategy around 1986 combined with the severity of the socioeconomic crisis left the country saddled with an unsustainable debt burden. The stock of external debt increased from less than 33 percent to more than 75 percent of GDP between 1985 and 1993 (Government of Cameroon 2003). In October 2000,

[4] Mostly known under its French acronym CEMAC for *Communauté Economique et Monétaire d'Afrique Centrale.*

Cameroon became eligible for debt relief under the Enhanced HIPC[5] Initiative. In this context, the government adopted a Poverty Reduction Strategy (PRS) in 2003. The strategy is designed to cut the number of poor by half by 2015 through strong and sustainable economic growth. Cameroon reached the Completion Point in May 2006, after three full years of implementation of the 2003 PRS. This achievement signals the satisfaction of Cameroon's development partners with the implementation of this strategy.

How much poverty reduction has this improved policy environment brought about? Preliminary analysis by the National Statistical Office based on the most recent household survey (2007) indicates that the overall incidence of poverty is still around 40 percent, about the same level as in 2001. The Gini index of inequality seems to have dropped a couple of percentage points from 41 percent in 2001 to 39 percent in 2007. These observations raise some interesting evaluative questions in terms of the social impact of economic growth in Cameroon. To what extent has the growth process been inclusive in Cameroon? What are the sources of observed variations (over time and across socioeconomic groups) in the distribution of economic welfare?

The purpose of this paper is to use available household level data, particularly the 2001 and 2007 surveys, to try to answer these questions using counterfactual decomposition of changes in the distribution of economic welfare. To put things into perspective, we present in section 2 a profile of growth, inequality and poverty for the period 1996-2007. In that section we use the Shapley decomposition to explain

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[5] HIPC stands for Heavily Indebted Poor Countries. This initiative was launched in 1996 by the International Development Association (IDA, the World Bank's fund designed to provide concessional credits and grants to the poorest countries) and the IMF. The initiative was enhanced in 1999 to tighten its link with poverty reduction and to widen its scope and make it more efficient (in terms of speed of relief delivery). Eligibility is based on three criteria: (1) qualify only for concessional assistance from IDA, (2) debt situation remains unsustainable after full application of traditional relief mechanisms, and (3) a track record of reforms combined with the development of a Poverty Reduction Strategy (presented in a document known as Poverty Reduction Strategy Paper or PRSP). The whole process entails reaching a *Decision Point* and a *Completion Point*. Two conditions must be met by a country to reach the Decision Point: (1) satisfactory preparation of an interim PRSP, and (2) satisfactory performance under the IMF's Poverty Reduction and Growth Facility (PRGF). At this point, the country gets conditional (on continued good performance) interim relief. At the Completion Point debt relief becomes irrevocable. Reaching this point requires the following: (1) maintain macroeconomic stability under a PGRF; (2) satisfactory implementation of a full PRSP for one year; (3) implementation of structural and social reforms agreed upon at the Decision Point.

variations in poverty in terms of changes in *per capita* expenditure and changes in inequality.

In section 3 we apply a novel approach to counterfactual decomposition of outcome distributions (Fortin, Lemieux and Firpo 2010; Firpo, Fortin and Lemieux 2009 a&b). In particular, using recentered influence function (RIF) regressions, the approach allows us to link the relevant growth incidence curve to house characteristics and to perform Oaxaca-Blinder type decomposition across quantiles. This way we can tell whether different factors (such as the distribution of characteristics or the returns to those characteristics) have different impacts at different points of the outcome distribution. We also use the same methodology to decompose the rural-urban gap in the distribution of economic welfare. For policymaking purposes, we need to understand the nature of the changes in the distribution of welfare associated with the process of economic growth. While the Shapley decomposition limits this understanding to changes in mean welfare and inequality, the generalized Oaxaca-Blinder decomposition allows a much richer analysis (Bourguignon and Ferreira 2005, Fortin, Lemieux and Firpo 2010)[6]. However, both methods base the identification of the determinants of differences across distributions of economic welfare on the comparison of *counterfactual distributions* with observed ones. Concluding remarks are made in section 4.

2. A Profile of Growth, Inequality and Poverty

In this section, we present a summary of the three datasets we use in the analysis. We also discuss the observed poverty outcomes and try to link them to changes in per capita expenditure and inequality.

Table 2.1. Distribution of Per Adult Equivalent Annual Expenditure in Cameroon (1996-2007)

	Mean	Lowest Decile	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
1996	243262.2	2.89	3.78	4.88	6.66	7.26	8.04	7.99	10.45	13.94	34.10
2001	372742.6	2.64	4.00	5.19	6.79	6.67	8.59	10.07	11.56	15.59	28.90
2007	432894.2	2.70	3.95	4.74	6.22	7.74	9.30	10.65	12.87	16.64	25.19

Source: Authors' Calculations (using data from the 1996, 2001 and 2007 household surveys)

[6] Within this framework outcome differentials are explained in terms of individual (or household) endowments (or characteristics) and the returns to those assets.

2.1. Evolution of Per Capita Income and Inequality

Table 2.1 presents a summary of the distribution of per adult equivalent[7] expenditure based on the 1996, 2001 and 2007 household surveys conducted by the National Statistical Office. All these surveys follow the sampling frame of the 1987 population census. The samples are stratified and the 1996 survey has the smallest sample size with 1,728 observations 36 percent of which represent the rural sector. The National Statistical Office (2002) has noted this under-representation of the rural areas in the 1996 household survey. For the other two surveys, the sample size is 10,992 observations for 2001 and 11,391 observations for 2007.

On the basis of the means reported in the second column of table 2.1, we find that (see table 2.2) the average per adult equivalent expenditure grew 5.4 percent per year over the period of 1996-2007 in nominal terms. Looking within sub-periods, the mean per adult equivalent expenditure grew by about 9 percent per year between 1996 and 2001, and by about 2.5 per year between 2001 and 2007. In real terms, these average rates of growth fall respectively to 1.9 percent, 4.1 percent and 0.5 percent. National account statistics tell a different story. The real per capita GDP is believed to have grown only by 1.57 percent per year between 1996 and 2001, and by 0.57 percent between 2001 and 2007 (National Statistical Office 2002, 2008).

Table 2.2. Growth in Average per Adult Equivalent Expenditure in Cameroon (1996-2007)

Period	Average Growth Rate (percentage)	
	Nominal	Real
1996-2001	9.0	4.1
2001-2007	2.5	0.5
1996-2007	5.4	1.9

Source: Authors' Calculations

[7] The underlying scale assigns weights to individual members of the household according to their age and gender. However there is no gender differential for children up to the age of 10. Thus children who are at most 1 year old get a weight of 0.255. Those with age between 1 and 3 years get assigned a weight of 0.45. Between the age of 4 and 6, the weight is 0.62 while it is 0.69 for the 7-10 age group. Starting from age 11, males get assigned the following weights: 0.86 between 11 and 14, 1.03 between 15 and 18, 1 between 19 and 50 and 0.79 above 50. All females between 11 and 50 get a weight of 0.76 and those above 50 get a weight of 0.66.

According to the National Statistical Office, there are at least five factors that explain the level of economic growth achieved between 1996 and 2001. These include: (1) a good performance of the export sector, particularly coffee, cocoa and cotton; (2) investments associated with the privatization program; (3) the expansion of the timber industry; (4) increased salaries in the public sector[8]; and (5) job creation and multiplier effects associated with the construction of the Chad-Cameroon pipeline. The National Statistical Office also explains that the poor performance of the economy between 2001 and 2007 is due mainly to the fact that growth occurred in low productivity sectors such as the urban informal sector and traditional agriculture.

The data presented in table 2.1 also reveal a significant amount of inequality in the distribution of per adult equivalent expenditure. The share of the richest decile is equal to almost 12 times that of the poorest decile in 1996, about 11 times in 2001 and 9.3 times in 2007. Furthermore we note that, for all three years, the share of expenditure of every decile up to the sixth is strictly less than its population share (10 percent). For the seventh decile, the share of expenditure is about 8 percent in 1996, and a little over 10 percent in 2001 and 2007. Table 2.3 shows that the Gini measure of overall inequality has hovered around 40 percent in 1996 and 2001 and declined slightly to about 39 percent in 2007.

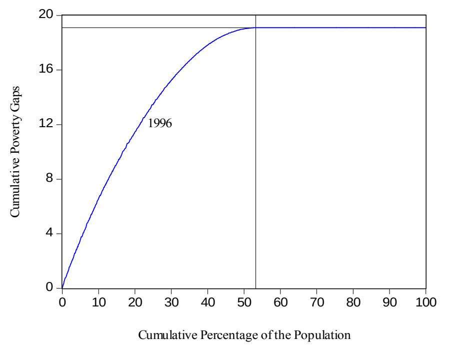
2.2. Changes in Poverty over Time

Figure 2.1 presents a picture summarizing the evolution of aggregate poverty from 1996 to 2007 based on TIP curves associated with poverty measures which are members of the Foster-Greer-Thorbecke (FGT) family. The acronym TIP stands for the *three I's of poverty* because the curve provides a graphical summary of *incidence*, *intensity* and *inequality* dimensions of aggregate poverty based on the distribution of poverty gaps (Jenkins and Lambert 1997)[9]. These dimensions are shown as follows: (1) the length of the non-horizontal section of the curve reveals poverty *incidence* ; (2) the *intensity* aspect of poverty is represented by the height of the curve; and (3) the degree of

[8] No indication is provided as to whether this salary increase reflected gains in productivity.
[9] This curve is constructed in four steps: (1) rank individuals from poorest to richest on the basis of the welfare indicator **y**; (2) compute the relative poverty gap of individual **i** as $\mathbf{g_i=max\{(1-y_i/z), 0\}}$ where **z** is the poverty line; (3) form the cumulative sum of the relative poverty gaps divided by population size; and (4) plot the resulting cumulative sum of poverty gaps as a function of the cumulative population share.

concavity of the non-horizontal section of the curve translates into the degree of *inequality* among the poor.

Figure 2.1. A Picture of Poverty in Cameroon, 1996-2007



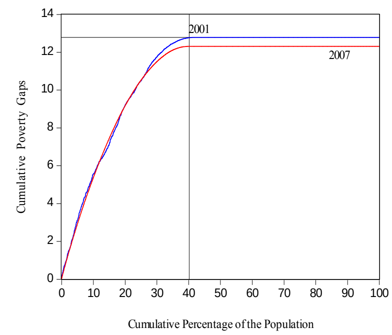


Table 2.3. A Profile of Poverty and Inequality, 1996-2007

	Overall			Urban			Rural		
	1996	2001	2007	1996	2001	2007	1996	2001	2007
Headcount	53.26	40.18	39.90	41.39	17.88	12.17	59.62	52.08	55.04
Poverty Gap	19.09	12.79	12.31	14.67	4.28	2.81	21.46	17.32	17.50
Squared Poverty Gap	9.00	5.55	5.03	6.92	1.59	0.96	10.12	7.67	7.24
Watts	26.66	17.38	16.11	20.55	5.48	3.51	29.94	23.72	22.99
Atkinson (1)	23.84	24.00	21.94	28.72	24.31	18.59	17.81	16.63	15.35
Atkinson(2)	38.16	38.82	35.82	45.63	38.25	31.85	30.38	29.72	25.93
Gini	40.63	40.41	38.96	44.91	40.71	35.19	34.60	33.15	32.23
MLD	27.23	27.45	24.77	33.86	27.85	20.56	19.61	18.19	16.66
Theil	31.75	33.75	27.88	37.64	35.39	22.87	21.61	19.36	18.76

Source: Authors' Calculations (MLD stands for Mean Log Deviation).

Figure 2.1 is consistent with the poverty outcomes presented in table 2.3, showing that poverty incidence dropped from about 53.3 percent in 1996 to about 40.2 percent and 40 percent in 2001 and 2007 respectively. The other three measures reported in that same table (the poverty gap, the squared poverty gap and the Watts measure) show a similar decline. These other three measures are members of the *additively decomposable*[10] class of poverty measures.

[10] This class of poverty measures is defined by the following expression: $P = \int_0^z \psi(y|z)f(y)dy$ where z is the poverty line, f(y) is the frequency density function of the welfare indicator y, and $\psi(y|z)$ is a convex and decreasing function measuring individual deprivation. The indicator of individual deprivation is equal to zero when the welfare level is greater or equal to the poverty line. The poverty measures are *additively separable* because the deprivation felt by an individual depends only on a fixed poverty line and her/his level of welfare and not on the welfare of other individuals in society. When the population is divided exhaustively into mutually exclusive socioeconomic groups, this class of measures allows one to compute

To begin to uncover some of the factors that might explain the observed changes in poverty between 1996 and 2007, we start from the fact that poverty indices are computed on the basis of a distribution of living standards which is fully characterized by its *mean* and the degree of *inequality* (as represented by the associated Lorenz curve). Any poverty measure therefore is a function of these two factors. Formally we write this as $P_t = P(\mu_t, L_t, z)$. In other words, poverty at time **t** is a function of the mean, $\boldsymbol{\mu_t}$, the Lorenz function, $\mathbf{L_t}$, and the poverty line, **z**, (assumed constant over time). We can use *counterfactual decompositions* to sort out the contribution of each of these factors to changes in overall poverty. The basic idea underlying such decompositions is to compare observed poverty outcomes to what they would have been under some counterfactual state defined by letting only one factor vary while holding all other factors fixed. In particular and given a fixed poverty line, we use the Shapley decomposition[11] method to identify the contributions of changes in the mean and relative inequality to the overall change in poverty.

To see clearly how this works in the context of poverty outcomes, we note that the marginal impact of the change in the mean of the distribution is equal to the change in poverty that would have been observed had relative inequality remained constant. The computation of this marginal effect is based on two counterfactual distributions. The first is obtained by scaling up the initial distribution of welfare (**y**) by a factor equal to the ratio $\frac{\mu_t}{\mu_{t-1}}$. This *distribution-neutral* transformation produces a counterfactual distribution with the same Lorenz function as the initial distribution and the same mean

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the overall poverty as a weighted average of poverty in each group. The weights here are equal to population shares. Such indices are *additively decomposable*.

[11] The Shapley decomposition is based on a microeconomic approach to distributive justice where the key issue is a fair assessment of the productive contributions of partners in a joint venture. The Shapley value of a participant is in general a solution to a cooperative game. If players join the game sequentially, the value of a player is her net addition to overall payoff when she joins. The Shapley value is the average contribution to the payoff over all possible orderings of the participants. The Shapley decomposition rule respects the following restrictions: (1) *Symmetry* or anonymity (the contribution assigned to any factor should not depend on its label or the way it is listed; (2) the rule should lead to exact or *additive decomposition*; and (3) the contribution of each factor is taken to be equal to its (first round) *marginal impact*. For more on the use of the Shapley value in inequality and poverty analysis, see Shorrocks (1999). Kakwani (2000) proposes a similar decomposition using an axiomatic approach. Datt and Ravallion (1992) offer a decomposition technique that splits a change in poverty between two dates into a growth component, a redistribution component and a residual. They interpret this residual as an interaction term.

as the end-period distribution[12]. The corresponding marginal effect is obtained by comparing poverty outcomes under this counterfactual with those observed in the base period. The second counterfactual is obtained by multiplying the level of welfare in the end period by the inverse of the above ratio. The value of the marginal effect associated with this counterfactual is based on the comparison of observed outcomes in the end period with the counterfactual ones. In order to respect anonymity, the Shapley contribution of changes in the mean to change in poverty is equal to the average of these two marginal effects. We refer to this term as the *scale component* of the Shapley decomposition.

Similarly, the computation of the contribution of changes in inequality to change in poverty, *ceteris paribus*, is based on transformations that are *size-neutral* to the extent they hold the mean of the distribution constant while changing the Lorenz function. This computation relies on the same counterfactuals discussed above[13].

Table 2.4. Shapley Decomposition of Poverty Outcomes, 1996-2007

	Overall	Scale	Inequality
		1996-2001	
Headcount	-13.08	-12.57	-0.51
Poverty Gap	-6.30	-6.18	-0.13
Squared Poverty Gap	-3.45	-3.47	0.02
Watts	-9.29	-9.35	0.06
		2001-2007	
Headcount	-0.28	-0.12	-0.16
Poverty Gap	-0.47	-0.06	-0.41
Squared Poverty Gap	-0.53	-0.03	-0.49
Watts	-1.27	-0.09	-1.17
		1996-2007	
Headcount	-13.36	-12.32	-1.04
Poverty Gap	-6.78	-6.23	-0.55
Squared Poverty Gap	-3.98	-3.52	-0.46
Watts	-10.55	-9.39	-1.16

Source: Authors' Calculations

[12] See Lambert (2001) and Kakwani and Son (2008) for applications of this transformation.

[13] In particular the contribution of changes in inequality, ceteris paribus, is equal to the average of the following two counterfactual comparisons. First, poverty outcomes for the distribution defined by the base mean and the end period Lorenz function are compared with baseline poverty outcome. Second, end period poverty outcomes are compared with those for the counterfactual defined by base Lorenz and the end period mean.

The results of our decomposition over the period 1996-2007 are reported in table 2.4. Those associated with the overall period, 1996-2007, suggest that on average both changes in the mean per adult equivalent expenditure and in relative inequality associated with the growth process have led to poverty reduction. The comparison of the magnitudes of the Shapley contributions indicates that the pure growth or *scale effect* dominates the *inequality effect*, except for the sub-period 2001-2007. The meager reduction in poverty observed in 2001-2007 is mostly due to the modest reduction in inequality.

2.3. Regional Disparity

Aggregate outcomes such as those discussed above can often hide a great deal of heterogeneity in the incidence of the growth process on poverty. This heterogeneity in impact also means that we can expect losers during spells of growth, even when poverty falls on average as we have observed above (Ravallion 2001). At this stage we limit our consideration of this issue to regional disparities[14]. Table A1 through A4 in the appendix present a profile of poverty and inequality for 12 regions of Cameroon (the two major cities Douala and Yaoundé, and the 10 provinces) for 2001 and 2007. The identification of winners and losers at the regional level is made on the basis of a comparison of regional outcomes to national outcomes. Focusing for instance on poverty incidence, we note that four provinces (Adamaoua, East, North and Far North) experienced a significant increase in poverty incidence between 2001 and 2007 while the trend in overall poverty was declining (although slightly). The two Northern provinces (North and Far North) saw the biggest increase. Poverty incidence increased by 13.6 and 9.6 percentage points respectively in the North and Far North. The increase was 6.4 for the Eastern province and 4.5 points for Adamaoua.

For each of the two years, 2001 and 2007, we also observe a deviation of regional poverty levels from the national average. It turns out that we can also use a two-way Shapley decomposition to identify proximate explanations for these poverty differences across regions (Kolenikov and Shorrocks 2005). Just as in the case of overall poverty,

[14] Later on we present some econometric results which will help us identify household characteristics that might explain outcomes described in this section.

regional poverty levels are fully determined by average real income and inequality in its distribution. Therefore, the Shapley contributions now indicate the influence of deviations of mean (real) income and inequality from the national level. This decomposition allows us to uncover the dominant factor between these two.

Our results for some important members of the class of additively decomposable poverty measures are presented in table 2.5 (a&b for 2001 and 2007 respectively[15]). There are six regions (the two major cities, and the coastal, western, southern and south-western provinces where poverty is generally below the national average in both 2001 and 2007. Poverty is above the national average for the other six regions. The overall pattern that emerges from these results is that, except for the western, southern and south-western provinces, the real income (scale) effect dominates (in magnitude) the inequality effect in 9 regions. Thus regions (among these 9) with lower poverty rates than the national average tend to have average real income higher than the national average. Similarly, average real income tends to be lower than the national average for those regions (out of 9) with higher poverty rates than the national average. Poverty levels in the West, South and South-West tend to be lower than the national average due to lower inequality.

The above results suggest that regional disparity in Cameroon is mostly due to differences in average real income, an indication of significant between-group inequality. The results of similar analysis applied to rural-urban differences for 1996, 2001 and 2007 are presented in table A5-A7 in the appendix. These results confirm the urban bias noted earlier to the extent that urban poverty is consistently below the national average while rural poverty is consistently above. A close look at the Shapley contributions reveals that rural poverty would be much higher than the national average if rural inequality were not lower than the national average. For instance in 2007, the incidence of rural poverty would have been about 21 percentage points higher than the national average if rural inequality had been at the same level as overall inequality. The observed difference stood at 15 points because the inequality effect was -6 percentage points.

[15] Here we focus on these two years because the data from the 1996 survey are organized around 4 regions only in addition to the 2 major cities.

Table 2.5a. Shapley Decomposition of Regional Differences in Poverty for 2001

	Headcount			Poverty Gap			Squared Poverty Gap			Watts		
	Difference	Scale	Inequality	Difference	Scale	Inequality	Difference	Scale	Inequality	Difference	Scale	Inequality
Douala	-29.29	-29.85	0.56	-10.71	-10.52	-0.19	-4.84	-4.64	-0.19	-14.76	-14.32	-0.45
Yaoundé	-26.84	-30.08	3.24	-10.13	-10.56	0.43	-4.70	-4.73	0.04	-14.10	-14.45	0.35
Adamaoua	8.20	14.54	-6.34	2.60	7.02	-4.42	0.83	3.70	-2.88	2.94	10.27	-7.33
Center	8.00	15.07	-7.07	2.19	6.42	-4.24	1.08	3.28	-2.21	3.67	9.40	-5.73
East	3.80	9.34	-5.54	2.58	5.70	-3.12	1.20	3.07	-1.88	3.48	8.43	-4.95
Far-North	16.11	22.73	-6.62	6.05	11.11	-5.05	2.62	5.96	-3.33	7.97	16.45	-8.48
CoastT	-4.70	2.47	-7.17	-2.70	0.71	-3.40	-1.38	0.36	-1.74	-3.95	1.02	-4.97
North	9.90	13.30	-3.40	2.71	6.36	-3.65	0.81	3.30	-2.49	3.05	9.24	-6.19
North-West	12.30	12.69	-0.39	8.11	7.08	1.03	5.15	4.10	1.05	13.45	11.00	2.45
West	0.15	10.17	-10.02	-1.69	4.33	-6.02	-1.36	2.21	-3.57	-3.19	6.22	-9.41
South	-8.63	3.94	-12.57	-5.43	1.61	-7.04	-3.13	0.76	-3.89	-8.34	2.24	-10.58
South-West	-6.36	-2.49	-3.86	-2.28	-1.05	-1.23	-1.04	-0.54	-0.50	-3.25	-1.53	-1.72

Source: Authors' Calculations

Table 2.5b. Shapley Decomposition of Regional Differences in Poverty for 2007

	Headcount			Poverty Gap			Squared Poverty Gap			Watts		
	Difference	Scale	Inequality	Difference	Scale	Inequality	Difference	Scale	Inequality	Difference	Scale	Inequality
Douala	-34.40	-26.66	-7.73	-11.44	-8.57	-2.87	-4.81	-3.51	-1.30	-15.10	-11.23	-3.88
Yaoundé	-33.96	-26.34	-7.62	-11.35	-8.54	-2.80	-4.79	-3.55	-1.23	-14.99	-11.25	-3.73
Adamaoua	13.05	17.73	-4.68	2.17	7.41	-5.23	0.39	3.69	-3.31	2.35	10.51	-8.16
Center	1.29	14.76	-13.46	-2.83	5.76	-8.59	-1.93	2.69	-4.62	-4.43	7.99	-12.43
East	10.51	16.43	-5.92	3.37	7.98	-4.61	1.20	4.25	-3.05	4.14	11.57	-7.44
Far-North	25.97	24.77	1.20	12.26	14.59	-2.33	6.18	8.43	-2.25	17.23	22.02	-4.79
Coast	-8.82	3.09	-11.91	-4.66	1.34	-6.00	-2.32	0.65	-2.97	-6.51	1.87	-8.38
North	23.76	24.15	-0.39	8.67	12.63	-3.96	3.55	6.68	-3.13	11.32	18.35	-7.03
North-West	11.10	9.66	1.44	4.30	5.61	-1.31	1.81	3.00	-1.19	5.67	8.15	-2.48
West	-10.95	2.85	-13.80	-5.68	0.98	-6.66	-2.76	0.47	-3.22	-7.87	1.36	-9.23
South	-10.64	-2.96	-7.68	-4.94	-1.27	-3.67	-2.38	-0.62	-1.76	-6.80	-1.77	-5.03
South-West	-12.39	-4.46	-7.93	-5.45	-1.78	-3.67	-2.55	-0.85	-1.70	-7.46	-2.47	-4.99

Source: Authors' Calculations

To assess the extent of between-group inequality in the distribution of economic welfare in Cameroon, we perform a threefold decomposition of the overall Gini measure of inequality following the framework proposed by Lambert and Aronson (1993). These authors explain that three basic components account for the overall inequality as measured by the Gini coefficient namely: (1) between group inequality, $\mathbf{G_B}$, (2) within group inequality, $\mathbf{G_W}$ (3) the extent of overlapping among subgroup distributions, $\mathbf{G_O}$ Let $\mathbf{G_Y}$ be the overall Gini for an income distribution for a population partitioned in **m** groups, then we have the following expression: $G_Y = G_B + G_W + G_O$. The within group component is known to be equal to a weighted sum of within group Gini coefficients where the weight of each group is equal to the product of its population share and its income share.

Our computation is based on a simple three-step procedure which Lambert and Aronson (1993) use to reveal the interrelation between these three components of the Gini coefficient. Like other decompositions used in this paper, this one also relies on a counterfactual comparison of distributions. Suppose that we start from a position of perfect equality where every individual (household) receives the overall mean income. We can introduce between group inequality by giving everybody, not the overall mean, but the mean income of her group. The Gini coefficient for this new distribution measures between group inequality.

Next consider the distribution obtained as follows. Keep individuals lined up by increasing order of group means. Thus all people from the poorest group will appear first in the income parade and members of the richest group will all appear last. Then, within each group, give people their actual incomes and sort them by increasing level of income within each group. The resulting distribution is such that the richest person in group (**k-1**) finds herself standing next to the poorest person in group **k**. By construction, this distribution accounts for both between group and within group inequality. We can net the between group component out by subtracting $\mathbf{G_B}$ from the concentration coefficient of this "lexicographic income parade"[16]. This operation yields an estimate of the within group component, $\mathbf{G_W}$.

[16] This terminology is from Lambert and Aronson (1993)

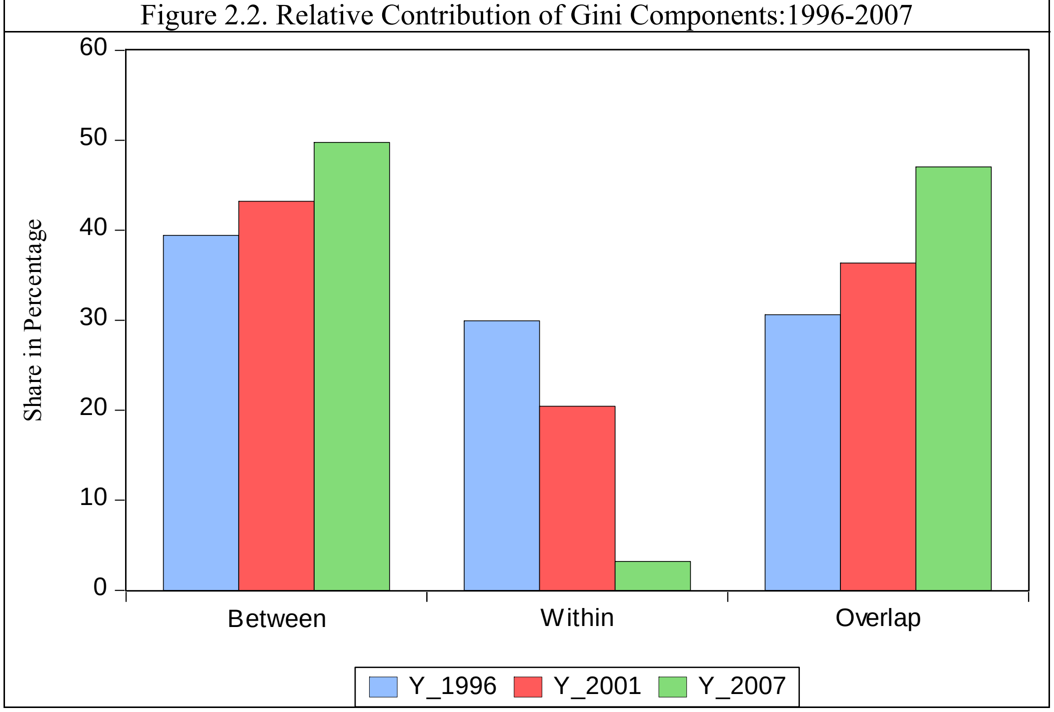
Finally, consider sorting individuals by increasing order of their actual income with no attention paid to group membership. People are now ranked from the overall poorest to the overall richest. To the extent that there is overlapping between subgroup distributions, some people will shift ranks relative to their positions in the lexicographic parade. The extent of this overlapping is measured by subtracting the concentration coefficient of the lexicographic distribution (which embeds both the between and within group components) from the overall Gini coefficient.

Table 2.6. A Threefold Decomposition of the Gini Measure of Inequality:1996-2007

	Level (in percentage)			Relative (in percentage)		
	1996	2001	2007	1996	2001	2007
Between-Group	16.02	17.46	19.38	39.43	43.21	49.75
Within-Group	12.17	8.26	1.25	29.95	20.45	3.21
Overlapping	12.44	14.69	18.33	30.62	36.35	47.05
Overall	40.63	40.41	38.96	100	100	100

Source:Authors' Calculations

Figure 2.2. Relative Contribution of Gini Components:1996-2007



Source: Authors' Calculations

Our application of this procedure to data for 1996, 2001 and 2007 led to results reported in both table 2.6 and figure 2.2. The decomposition for 2001 and 2007 is based on the same groups listed in table 2.5. As noted earlier, the data from the 1996 survey has a different grouping. These results confirm the conclusion we reached earlier on the basis of Shapley analysis of regional differences in Poverty. Between group inequality is indeed a major component of overall inequality (as measured by the Gini Coefficient) in Cameroon. This component has increased from 39 percent of the total in 1996 to almost 50 percent in 2007. It represented 43 percent of total inequality in 2001. These results also reveal that there is significant overlapping between regional distributions and a low level of within group inequality. In addition, within group inequality has been declining significantly over time. It accounted for about 30 percent of total inequality in 1996, 20 percent in 2001 and dropped to about 3 percent in 2007.

Table 2.7. Contribution of Location to Income Inequality

	Rural-Urban	Region	Rural-Urban &Region
1996	0.03	0.10	0.10
2001	0.18	0.17	0.22
2007	0.30	0.35	0.40

Source: Authors' Calculations

Finally, we use simple regression analysis to decompose the variance of the logarithm of per adult equivalent expenditure. To do this, we run regressions the logarithm of per adult equivalent expenditure only on a set of dummy variables indicating the area of residence of the household. It is known that the R-squared from such a regression measures the proportion of the variation in the dependent variable (log of expenditure) explained by the location dummies (Benjamin, Brandt and Giles 2005). We consider three different specifications for each of the three years: the rural-urban divide alone, the regions only and the interaction between regional dummies and the rural-urban indicator. The results are presented in table 2.7. These results confirm that there is significant regional disparity in Cameroon and it has been growing over time. In 1996, rural-urban location accounted only for 3 percent of the variance of log per adult equivalent expenditure. In 2007, this proportion has increased to 30 percent. The regional dummies account for 10 percent of the variation in 1996 versus 35 percent in

2007. The interaction between the two types of location dummies explains 10 percent of the variation in log per adult equivalent expenditure in 1996 and 40 percent in 2007.

3. A Counterfactual Decomposition of Growth Incidence

Figure 3.1.Growth Incidence Curve, 2001-2007

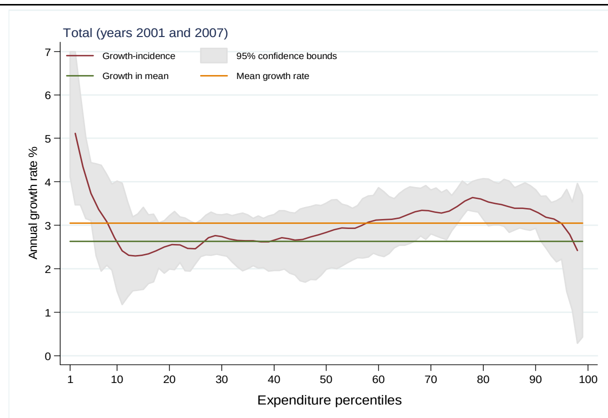


Figure 3.1 presents the Growth Incidence Curve[17] (GIC) for the period 2001-2007. This curve shows how the distribution of expenditure changes at each quantile between 2001 and 2007. Presumably this is an outcome of the underlying Poverty Reduction Strategy. The curve reveals some heterogeneity in the impact of growth on the living standards. People located at the bottom of the distribution up to the 10th percentile have experienced an income growth greater than average and so have most of the people above the median, except at the very top of the distribution. Between the 10th and about the 30th percentiles, incomes grew at a rate below average. Finally the segment of the population located between the 30th and the 50th percentiles experienced an income growth rate equal to the growth rate of the average income. In this section we use influence functions to link this pattern of growth to household characteristics and to perform Oaxaca-Blinder type decompositions. This decomposition framework is designed to help identify the effects of household (or individual) characteristics and the

[17] As defined by Ravallion and Chen (2003), the Growth Incidence Curve shows the growth rate of an indicator of the living standard (e.g. income or expenditure) at the p^th quantile of the size distribution of that indicator. It is formally defined by the following expression $g(p) = dln(y)$ where $= \int_0^y f(v)dv$, and f(·) is the density function characterizing the distribution of the living standard indicator.

returns to those characteristics on the distribution of economic welfare[18]. We first explain the structure of the framework along with its empirical implementation[19]. We then discuss the results of its application to the data at hand.

3.1. The Oaxaca-Blinder Decomposition Framework

Just as in the case of the Shapley decomposition, the main *objective of the Oaxaca-Blinder method is to identify the factors that might account for changes in the distribution of outcomes from one state of the world to another*. In the context of policy impact analysis, individual outcomes are viewed as pay-offs to participation and type, where type is defined by observable and unobservable characteristics. Differences in outcome distributions therefore reflect differences in pay-off structure and differences in the distribution of characteristics. The Oaxaca-Blinder decomposition method is commonly used to split the overall difference in the distribution of outcomes between two different states of the world into a component attributable to differences in pay-off structure and another due to differences in the distribution of observable characteristics.

Within this framework, we need a model linking the outcome of interest to individual (or household) characteristics. We therefore maintain the assumption that the welfare indicator **y** (e.g. real per capita expenditure in our case) has a joint distribution with household characteristics (such as age, education and occupation of the head of household, area of residence and family size) represented by a vector **x**. The approach applies to both changes in summary statistics and in whole distributions. More specifically, we are interested in comparing features of an outcome distribution under two mutually exclusive states of the world say, **j** and **s**. We formally write the outcome equation as follows.

$$y_t = g_t(x, \varepsilon),\ t = j, s. \qquad (3.1)$$

[18] In particular Ravallion (2001) argues that disparities in *access* to human and physical capital, and differences in *returns* to such assets are the main determinants of income inequality. Furthermore these disparities are most likely to inhibit overall growth prospects.

[19] Our presentation of the structure of this framework follows closely Fortin, Lemieux and Firpo (2010).

where ε represents unobservable factors. This specification implies that the outcome distribution can vary between the two states due to: (1) differences in the outcome structure functions $\mathbf{g_t(\cdot)}$, (2) differences in the distribution of observable characteristics ($\mathbf{x}$), and (3) differences in unobservable characteristics ($\boldsymbol{\varepsilon}$).

Like many other decomposition techniques, the Oaxaca-Blinder method relies on estimating some counterfactual distribution of outcomes such as the distribution of outcomes that individuals observed in state **s** would have experienced under the conditions prevailing in state **j**. Let **t** stand for an observable indicator of the prevailing state, $y_{j|t=s}$ and $y_{s|t=j}$ represent counterfactual outcomes for state **s** and state **j** respectively. Distributional statistics such as the mean, the variance, various quantiles, and measures of inequality such as the Gini coefficient or members of the generalized entropy family can be thought of as real-valued *functionals* of the relevant distributions[20]. Let $F_{y_j|t=s}$ stand for the distribution of the (potential) outcome $\mathbf{y_j}$ for individuals in state **s**. We will express any distributional statistic associated with this distribution as: $\theta\left(F_{y_j|t=s}\right)$. The overall difference in the distribution of outcomes between the states **j** and **s** can be written in terms of this statistic as follows (Fortin, Lemieux and Firpo 2010).

$$\Delta_O^\theta = \theta\left(F_{y_s|t=s}\right) - \theta\left(F_{y_j|t=j}\right) \tag{3.2}$$

Splitting this overall difference in outcomes between the two states into a component attributable to differences in observed characteristics of agents, and a component attributable to the outcome structure, entails a comparison of actual and counterfactual outcome distributions. In particular we used the above counterfactual for state **s** to obtain the following aggregate decomposition.

$$\Delta_O^\theta = \left[\theta\left(F_{y_s|t=s}\right) - \theta\left(F_{y_j|t=s}\right)\right] + \left[\theta\left(F_{y_j|t=s}\right) - \theta\left(F_{y_j|t=j}\right)\right] \tag{3.3}$$

Following Fortin, Lemieux and Firpo (2010) we note this decomposition as: $\Delta_O^\theta = \Delta_S^\theta + \Delta_X^\theta$. The first component of this aggregate decomposition (Δ_S^θ) is known as the outcome structure effect or the *structural effect* of moving from the outcome distribution prevailing in state **j** to the one in state **s**. The second component (Δ_X^θ) is the *composition*

[20] A functional is a rule that maps every distribution in its domain into a real number (Wilcox 2005)

effect. Bourguignon and Ferreira (2005) refer to these two effects respectively as the price-behavioral effect (or *price effect* for short) and the *endowment effect*.

The outcome model (3.1) suggests that conditional on the observable characteristics, **x**, the outcome distribution depends only on the function $\mathbf{g_t(\cdot)}$ and the distribution of the unobservable characteristics $\boldsymbol{\varepsilon}$. If the composition effect represents that part of the outcome differential due to observable characteristics only, for things to add up, the structural effect must account for differences in $\mathbf{g_t(\cdot)}$ and in the distribution of $\boldsymbol{\varepsilon}$. The identification and estimation of these two effects rest on a factorization of the joint distribution of outcomes and characteristics and a *ceteris paribus* condition which is satisfied if there are no general equilibrium effects and unobservable factors are conditionally independent of the state of the world, given the observables[21].

DiNardo, Fortin and Lemieux (1996) show that the counterfactual distribution, $F_{y_j|t=s}$, can be estimated by properly reweighing the distribution of covariates in state **j**. Using a slightly simplified notation, one can express this counterfactual as follows.

$$F_{y_j|t=s}(y) = \int F_{y_j|x_j}(y|x)\mathrm{w}(x)dF_{x_j}(x) \qquad (3.4)$$

where the reweighing factor is equal to: $\mathrm{w}(x) = \frac{dF_{x_s}(x)}{dF_{x_j}(x)} = \frac{P(t=s|x)}{1-P(t=s|x)} \cdot \frac{1-\pi}{\pi}$. These weights are proportional to the conditional odds of being observed in state **s**. The proportionality factor depends on π which is the proportion of cases observed in state **s**. One can easily

[21] To see clearly what is involved, note that the law of total probability implies that one can derive the distribution of $\mathbf{y_j|t=j}$ from a factorization of the conditional joint distribution $\mathbf{y_j}$ and the covariates **x** as follows: $F_{y_j|t=j}(v) = \int F_{y_j|x,t=j}(v|x=\ell) \cdot dF_{x|t=j}(\ell)$. The counterfactual distribution which underpins the aggregate decomposition in (3.3) is the distribution of outcomes that would prevail in state **s** if observable characteristics were rewarded as in state **j**, *ceteris paribus*. It is equal to the following: $F_{y_j|t=s}(v) = \int F_{y_j|x,t=j}(v|x=\ell) \cdot dF_{x|t=s}(\ell)$. This counterfactual can be obtained by replacing in the above factorization the distribution of observables in state **j** ($F_{x|t=j}$) with that of state **s** ($F_{x|t=s}$), while holding constant the conditional outcome distribution of state **j** ($F_{y_j|x,t=j}$). Given that this conditional outcome distribution depends on both the outcome structure $\mathbf{g_t(\cdot)}$ and the distribution of $\boldsymbol{\varepsilon}$, if there are no general equilibrium effects, the outcome structure would be invariant to changes in the distribution of covariates. In addition, if the distribution of unobservables is the same in both states of the world (i.e. conditional independence holds), changing the distribution of the observed characteristics would not affect that of the unobservables. Under these conditions therefore, the terms of the aggregate Oaxaca-Blinder decomposition are identifiable and can be consistently estimated (Fortin, Lemieux and Firpo 2010).

compute the reweighing factor on the basis of a probability model such as logit or probit[22].

The classic Oaxaca-Blinder decomposition applies only to differences in the mean of the outcome variable and assumes that the outcome variable is a linear function of individual characteristics (observable or not). In addition, this variant of the method assumes that the conditional mean of the unobservables given observables is equal to zero. These assumptions imply that the conditional expectation of the outcome variable is also a linear function of the covariates while the unconditional expectation of the same variable is a linear combination of the expected values of the covariates. The coefficients spanning this combination are obtained from a regression of the outcome variable on the covariates. The expected values of the covariates are estimated by the corresponding sample means[23].

The linearity assumption makes it easier to compute the contribution of each covariate to each component of the aggregate decomposition. Fortin, Lemieux and Firpo (2010) explain that a decomposition approach provides a detailed decomposition when it allows one to apportion the composition effect or the structural effect into components attributable to each explanatory variable[24]. The contribution of each explanatory variable

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[22] In general the aggregate decomposition procedure follows three basic steps (Fortin, Lemieux and Firpo 2010): (1) pool the data for states **j** and **s** to run a logit or probit model for belonging to state **s**; (2) estimate the reweighing factor **w(x)** for observations in **j** using the predicted probability of belonging to **j** and **s**; (3) compute the counterfactual statistic of interest using observations from the **j** sample reweighted by the estimated reweighing factor.

[23] In terms of the general framework discussed in this section, linearity combined with the assumption of mean independence implies that the expected value of the outcome variable in state t is equal to: $E(y_t|t) = E(x|t)\beta_t, t = j, s$. The mean of the counterfactual distribution $F_{y_j|t=s}$ can therefore be written as: $\mu\left(F_{y_j|t=s}\right) = E(x|t = s)\beta_j$. The corresponding structural effect is: $\Delta_S^{\mu} = \mu\left(F_{y_s|t=s}\right) - \mu\left(F_{y_j|t=s}\right) = E(x|t = s)(\beta_s - \beta_j)$, and the composition effect is: $\Delta_X^{\mu} = \mu\left(F_{y_j|t=s}\right) - \mu\left(F_{y_j|t=j}\right) = [E(x|t = s) - E(x|t = j)]\beta_j$.

[24] Let x_k and β_k reperesent the k^{th} element of x and β respectively. Then to structural effect can be written as the sum of individual contributions : $\Delta_S^{\mu} = \sum_{k=1}^{m} E(x_k|t = s)(\beta_{sk} - \beta_{jk})$. Similarly, the compostion effect can be written as the sum of partial composition effects: $\Delta_X^{\mu} = \sum_{k=1}^{m}[E(x_k|t = s) - E(x_k|t = j)]\beta_{jk}$. Firpo, Fortin and Lemieux (2007) note two limitations of the classic Oaxaca-Blinder decomposition. The contribution of each covariate to the structural effect is highly sensitive to the choice of the base case. Furthermore, the decomposition provides consistent estimates only when the assumption of linearity is valid. One should therefore consider using reweighing even in this classical case to protect against misspecifications.

to the composition effect is analogous to what Rothe (2010) calls a "*partial composition effect*"[25].

For the purpose of our study, we would like to account for impact heterogeneity along the growth incidence curve depicted in figure 3.1. We note that in the absence of panel data spanning the growth episode under consideration, it is impossible to identify impact for a particular individual or household[26] , the identification and computation of the local impact of growth relies therefore on the assumption of *anonymity*[27] and compares growth rates across quantiles[28] based on cross-sectional data. This approach is essentially the same as that underlying the identification of quantile treatment effects (QTE) in the context of treatment effect analysis. Here, the *anonymity* assumption plays the same role as that of *rank preservation* across treatment status in the case of QTEs[29].

To try to uncover what might be driving the pattern of growth incidence we need a way of linking marginal (unconditional) quantiles to household characteristics that also allows us to perform Oaxaca-Blinder type decompositions. *Recentered influence function* (RIF) regression offers a simple way of establishing this link and performing both aggregate and detailed decompositions for any statistic for which one can compute an *influence function* (Fortin, Lemieux and Firpo 2010). An influence function is the derivative of a functional. Thus the derivative of a distributional statistic **θ(F**) is called

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25 This is the effect of a counterfactual change in the marginal distribution of a single covariate on the unconditional distribution of an outcome variable, ceteris paribus. Rothe (2010) interprets the ceteris paribus condition in terms of rank invariance. In other words, the counterfactual change in the marginal distribution of the relevant covariate is constructed in such a way that the joint distribution of ranks is unaffected.

26 This is an instance of missing data problem characterizing the identification issue in the context treatment effect analysis.

27 This assumption, also referred to as *symmetry*, implies that when comparing distributions of outcomes the position of a particular individual in one distribution is irrelevant (Carneiro, Hansen and Heckman 2002).

28 Quantile (or fractile) is a cut-off value of a variable such that a given fraction of values lie at or below the cut-off point (Freund and Williams 1991). For instance, the performance of a student on a standardized test is said to be at the $\boldsymbol{\tau}^{\mathbf{th}}$ quantile if a proportion $\boldsymbol{\tau}$ of scores in the reference group are less than or equal to hers. Formally, let **y** be a random variable with probability distribution function $F(z) = P(y \leq z)$. The $\boldsymbol{\tau}^{\mathbf{th}}$ quantile of **y** is the smallest value of **y**, say $\mathbf{q}(\boldsymbol{\tau})$ such that: $F(z) \geq \tau, 0 < \tau < 1$. Equivalently we write: $q(\tau) = \{z: F(z) \geq \tau\} = F^{-1}(\tau)$.

29 *Rank preservation* across two alternative states of the world (or rank invariance) means the outcome at the $\boldsymbol{\tau}^{\mathbf{th}}$ quantile in the outcome distribution for one state has its counterpart at the same location in the outcome distribution for the other states. When rank preservation fails, the QTE approach identifies and estimates the difference between the quantiles and not the quantiles of the difference in outcomes (Bitler et al. 2006).

the influence function of **θ** at **F** (where **F** is the distribution function of the random variable **y**). We note this function as **IF(y;θ, F)**. The influence function of the $\boldsymbol{\tau}^{\text{th}}$ quantile of the distribution of **y** is given by the following expression (Firpo, Fortin and Lemieux 2009a).

$$IF(y;\ q_\tau) = \frac{[\tau - I(y \leq q_\tau)]}{f_y(q_\tau)} \tag{3.5}$$

where the distribution function is kept implicit, **I(·)** is an indicator function for whether the outcome variable is less than or equal to the $\boldsymbol{\tau}^{\text{th}}$ quantile, and $f_y(q_\tau)$ is the density function of y evaluated at the $\boldsymbol{\tau}^{\text{th}}$ quantile.

Fripo, Fortin and Lemieux (2009a) define the recentered or rescaled influence function (RIF) as the leading terms of a von Mises (1947) linear approximation of the associated functional. It is equal to the functional plus the corresponding influence function. Given that the expected value of the influence function is equal to zero, the expected value of the RIF is equal to the corresponding distributional statistic. In other words, $\theta(F_y) = E[RIF(y;\ \theta, F_y)]$. The rescaled influence function of the $\boldsymbol{\tau}^{\text{th}}$ quantile of the distribution of **y** is:

$$RIF(y;\ q_\tau) = q_\tau + IF(y;\ q_\tau) = q_\tau + \frac{[\tau - I(y \leq q_\tau)]}{f_y(q_\tau)} \tag{3.6}$$

By the law of iterated expectation the distributional statistic of interest can be written as the conditional expectation of the rescaled influence function (given the observable covariates). This conditional expectation is known as a RIF regression. We express the RIF regression for the $\boldsymbol{\tau}^{\text{th}}$ quantile of the distribution of **y**, as: $E[RIF(y; q_\tau)|x]$ so that the unconditional or marginal quantile is equal to:

$$q_\tau = \int E\big[RIF\big(y;\ q_\tau, F_y\big)\big|x\big]dF(x) \tag{3.7}$$

In the empirical implementation of this approach, we follow Firpo, Fortin and Lemieux (2007) and work with a linear approximation of the RIF regression of the $\boldsymbol{\tau}^{\text{th}}$ quantile. These authors explain that, since the expected value of the approximation error is zero, the expected value of the linear approximation of the RIF regression is equal to the expected value of the true conditional expectation. This fact makes the extension of the standard Oaxaca-Blinder decomposition to RIF regressions both simple and meaningful.

To be more specific, let $\boldsymbol{\gamma}^{\mathbf{q\tau}}$ be the estimated coefficients from a regression of RIF(y;q_τ) on **x**. Following the standard Oaxaca-Blinder approach, the structural effect can be written as

$$\Delta_S^{q_\tau} = E(x|t=s) \cdot (\gamma_s^{q_\tau} - \gamma_j^{q_\tau}) \tag{3.8}$$

The composition effect is

$$\Delta_X^{q_\tau} = [E(x|t=s) - E(x|t=j)] \cdot \gamma_j^{q_\tau} \tag{3.9}$$

This decomposition may involve a bias since the linear specification is only a local approximation that may not hold in the case of large changes in covariates[30]. The solution to this problem is to combine reweighing with RIF regression and compute the structural effect as follows

$$\Delta_S^{q_\tau} = E(x|t=s) \cdot (\gamma_s^{q_\tau} - \gamma_c^{q_\tau}) \tag{3.10}$$

where $\gamma_c^{q_\tau}$ is the vector of coefficients from a RIF regression on state **j** sample reweighted to have the same distribution of covariates as in group **s**. Reweighing ensures that $(\gamma_s^{q_\tau} - \gamma_c^{q_\tau})$ reflects a true change in the outcome structure.

Now, the expression for the composition effect includes the approximation error

$$\Delta_X^{q_\tau} = [E(x|t=s) - E(x|t=j)] \cdot \gamma_j^{q_\tau} + E(x|t=s)(\gamma_c^{q_\tau} - \gamma_j^{q_\tau}) \tag{3.11}$$

The use of a linear approximation of the RIF regression also makes it easier to separate out the contribution of different subsets of covariates to the various elements of the aggregate decomposition. For the composition effect, we have

$$\Delta_X^{q_\tau} = \sum_{k=1}^{m} [E(x_k|t=s) - E(x_k|t=j)]\gamma_{jk}^{q_\tau} + \sum_{k=1}^{m} E(x_k|t=s)(\gamma_{ck}^{q_\tau} - \gamma_{jk}^{q_\tau}) \tag{3.12}$$

Similarly, the structural effect can be written as.

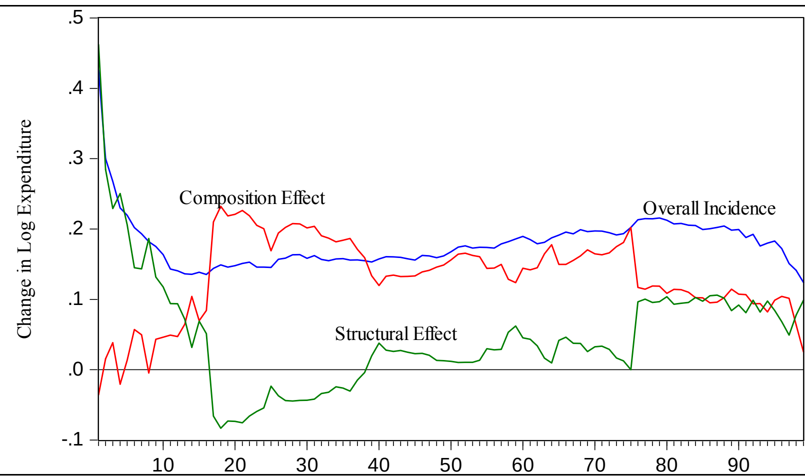
$$\Delta_S^{q_\tau} = \sum_{k=2}^{m} E(x_k|t=s)(\gamma_{sk}^{q_\tau} - \gamma_{ck}^{q_\tau}) + (\gamma_{s1}^{q_\tau} - \gamma_{c1}^{q_\tau}) \tag{3.13}$$

[30] In particular, $\gamma_s^{q_\tau}$ and $\gamma_j^{q_\tau}$ may differ just because their estimation is based on different distributions of the covariates **x**, even if the outcome structure remains unchanged (Firpo, Fortin and Lemieux 2009a).

3.2. Empirical Results

In this section of the paper, we focus on three sets of empirical results. First, we examine the coefficients of both the OLS and unconditional quantile regressions of log expenditure on household characteristics. As noted earlier, RIF regressions allow us to link the growth incidence curve to household characteristics, and to account for heterogeneity of impact across quantiles. Next, we consider both the aggregate and detailed decompositions of the growth incidence curve into composition and structural effects. Finally, we take a closer look at the rural-urban differential in living standards to try to identify the proximate determinants of the difference in welfare between the rural and urban sectors.

Figure 3.2 A Decomposition of Growth Incidence between 2001 and 2007



Returns to Selected Covariates

We consider four broad categories of characteristics: (1) *Demographics* (gender of household head, age of household head, and household composition in terms of proportions of various age groups up to age 25); (2) *Household and community assets* (years of schooling of head of household, land ownership, access to credit, at least one migrant in household, distance to nearest hospital, distance to nearest tarred road); (3)

Sector of employment (public sector, formal private sector, smallholder agriculture, informal non-agriculture, unemployed; and (4) *Area/province of residence*[31].

Our estimates of the marginal impact of each characteristic on household welfare in 2001 and 2007 are reported in tables B1 and B2 in the appendix. These tables show the coefficients and the associated standard errors for OLS and selected unconditional quantile regressions. We focus first on the OLS results. All demographic variables are statistically significant. As expected, an increase in any component of household membership reduces welfare. The male dummy variable has a negative sign in 2001 and a positive one in 2007. However, the 2007 coefficient is not significantly different from zero. Thus male-headed households do not necessary fare better than the reference female-headed households in either year, other things being equal. Among the remaining non-geographical characteristics, the following have the highest positive and statistically significant impact on household welfare: (1) formal sector employment (public or private), (2) access to credit and (3) years of schooling of the head of household. Having at least one migrant in the household has no significant impact on welfare in either year. Similarly, land ownership does not seem to make any difference, on average. The coefficient for agricultural employment is statistically significant in both years but has a negative sign. This is certainly another manifestation of urban bias noted earlier. Indeed, these regression results confirm that urban residence has a strong positive impact on welfare.

The OLS results discussed above give only the average impact of the characteristic of interest on household welfare. We now consider results from RIF regressions to learn how these impacts vary across quantiles. It is much easier to deal with plots of the coefficient estimates at various quantiles rather than the estimates themselves. To keep our story manageable, we focus on three groups of covariates namely household assets (education of head, access to credit, land ownership and having at least one migrant), sector of employment and area of residence (urban-rural). The effects of these characteristics are plotted in figures B1 through B5 (in appendix B).

[31] Our choice of dummy variables implies that the reference household (conditional on characteristics represented by continuous variables) lives in the rural area of the central province and has head who is female and out of the labor force, no access to credit and no migrant.

Figure B1 shows plots of the unconditional quantile regression coefficients for education and access to credit. Returns to education (in terms of real per adult equivalent expenditure) are positive and statistically significant across all quantiles. Not surprisingly, economic welfare increases with education over the whole distribution. In 2001, the impact of education increases faster at the lower end of the distribution up to the 17th percentile. After that point the quantile function remains more or less flat up to the median. It assumes a U-shape in the top-end of the distribution (between the median and the 95th percentile). This profile implies that, for the year 2001 education enhances inequality in the lower and upper ends of the distribution. The pattern is different for the year 2007 where the impact of education is more or less increasing over the entire distribution. Thus education is thoroughly inequality enhancing in 2007. Comparing both years, we note that (with the exception of the lower end of the distribution and the segment between the 66th and 87th percentiles) the impact of education is significantly higher in 2001 than in 2007. This could be a manifestation of the lack of economic growth experienced by the country over that period. Indeed the lack of employment opportunities for the educated is a latent source of social tension in Cameroon.

The quantile plot for the returns to access to credit has an inverse U-shape in the low-end of the distribution (up to the 56th percentile) in 2001. Thus access to credit in 2001 increases inequality in the lower end of the distribution (up to the 25th percentile) and dampens inequality between the 25th and the 56th percentiles. In 2007, the effect has a U-shape in the same range of the distribution. The 2001 curve dominates the 2007 one. The effect of having access to credit is flat at the upper end of the distribution (i.e. past the median) and there is no significant difference between the two years.

Figure B2 show the marginal impacts of land ownership and migration. Overall, land ownership has a very small positive impact on household welfare in the low-end of the distribution, particularly in 2007 and at the upper end of the distribution. Having at least one migrant in the household in 2001 made no significant difference for most households over the entire distribution of welfare except in the neighborhood of the 10th percentile where the impact is statistically significant and negative. No other coefficient underlying the quantile curve is significantly different from zero in a statistical sense. But most of these coefficients are different from zero and statistically significant in 2007.

In particular having a migrant in the household in 2007 has a positive impact on welfare in the lowest end of the distribution (up to the 10th percentile) and between the 60th and the 97th percentile. In addition, it contributes to increasing inequality in the lower parts of those segments of the distribution of welfare in 2007.

The effects of formal sector of employment are presented in figures B3 and B4. As far as employment in the private sector is concerned, the left panel of figure B3 reveals that returns to this attribute are positive in 2001 for households located beyond the 12th percentile. In 2007, these returns are negative for most of that range up to the 75th percentile. For the lowest end of the distribution, private sector employment brings positive returns only in 2007. The pattern of returns is similar for the public sector except that returns for 2007 are negative only over a very short range (from the 13th to the 24th percentile). A comparison of the two sectors in figure B4 shows that there is a reversal in the relative pattern of the returns to public and formal private sector employment between 2001 and 2007. In 2001 the curve for the private sector dominates that for the public sector. In 2007, the two curves are basically indistinguishable up to the 25th percentile then the public sector overtakes the private sector all the way up to the 95th percentile and both curves merge again. The configuration of these quantile curves suggests two things. First, there is no advantage for the poor to be engaged in the formal sector. Second the sluggish growth experienced between 2001 and 2007 may have hurt households engaged in the private sector more that those in the public sector.

We note from figure B5 that households engaged in agriculture are worse off across quantiles and years, than those employed in the other sectors of the economy[32]. In 2001, the returns to agriculture are positive only between the 14th and 36th percentiles. In 2007, this impact is positive only from the 96th percentile. The configuration of the two curves implies that the penalty associated with being engaged in agriculture hurts the households at the lower end of the distribution more than those at the top. The same figure reports the marginal impact of urban residence on welfare. In both years, the quantile curves have generally an inverted U-shape (first rising and then falling). This suggests that urban residence increases inequality in the low end of the distribution and decreases it in the top end. This pattern is more pronounced in 2007 than in 2001. The

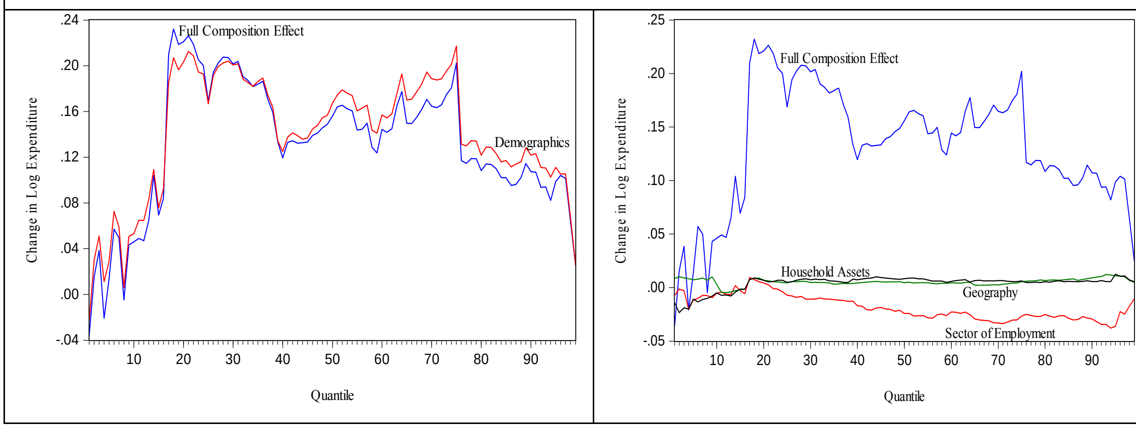
[32] The results for the informal sector, not shown, have the same pattern as those for smallholder agriculture.

curve for 2007 dominates that for 2001 in the 35th to 97th percentile range. This pattern of unconditional quantile regression coefficients confirms that urban households are generally better off than their rural counterparts and that this urban bias has been increasing over time.

Decomposition of the Growth Incidence Curve

Figure 3.2 shows a decomposition of the total variation in the distribution of log per capita expenditure (essentially the GIC) into two components. The first component is due to changes in the distribution of characteristics while the second represents the contribution of changes in the distribution of returns to those characteristics. These two components pull in opposite directions from the lowest percentile to the 76th. Past this point, both effects are more or less the same. Overall, the structural effect has a U-shape while the composition effect has an inverted U-shape. The structural effect dominates at the lowest end of the distribution while the composition effect dominates in the middle, from the 12th to the 76th percentile. Thus, the structural effect tends to decrease inequality at the lowest end of the distribution while the composition effect tends to increase it.

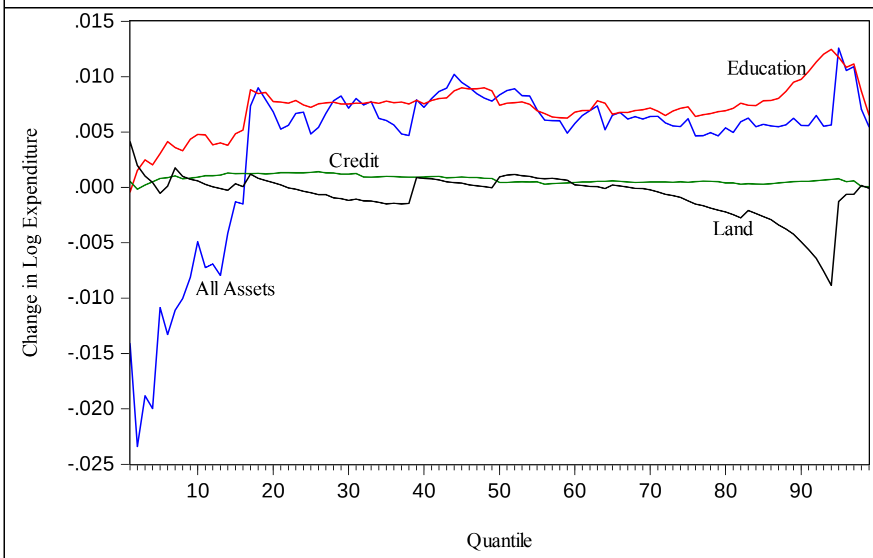
Figure 3.3: Composition Effects



Once we account for the composition effect, the profile of the growth incidence curve is closer to that of the structural effect than that of the composition effect. The effect of characteristics is positive and shows a slight decline across quantiles. The effect of returns to those characteristics is negative for households located between the 14th and the 39th percentiles. The configuration of the three curves implies that the level of the

GIC is driven by the composition effect while the shape of the same GIC is explained mostly by the structural effect. In particular, the fact that people located at the bottom of the distribution up to the 10th percentile have experienced an income growth greater than average is due to the structural effect while the gains beyond that point are mainly due to the composition effect. Recall that, according to the GIC depicted by figure 3.1, most of the people above the median, except at the very top of the distribution also experienced an income growth above average. This outcome is due to the composition effect.

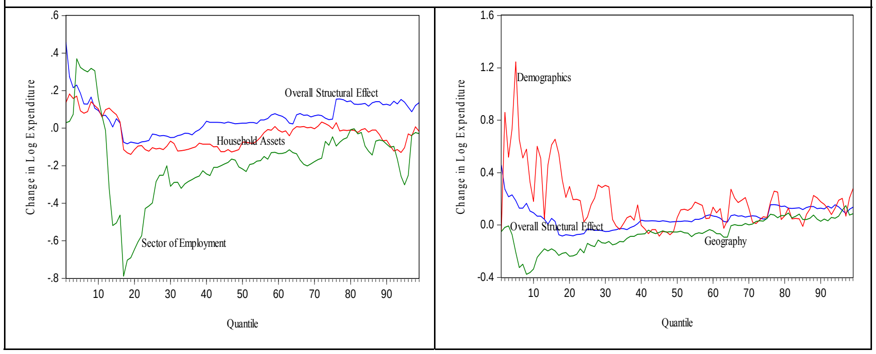
Figure 3.4: Composition Effects of Household Assets



What drives the composition and the structural effects? To try to understand the potential factors that determine these two components of the aggregate decomposition, we further disaggregate these two components on the basis of sets of covariates. The results are presented in figures 3.3-3.5. The left panel of figure 3.3 compares the full composition effect to the contribution of household demographics to this effect. The right panel compares the same full effect and the contributions of household assets, sector of employment and geography. These results clearly show that both the level and the dispersion of the full composition effect are mostly accounted for by household demographics.

Figure 3.4 shows the contributions of various household assets to the composition effect. The figure reveals that the contribution of assets to the composition effect is mostly accounted for by changes in the distribution of years of schooling.

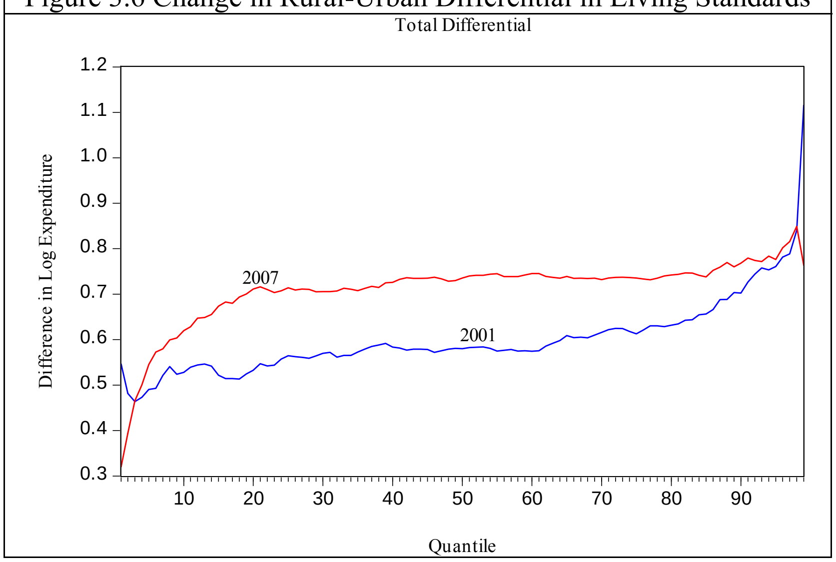
Figure 3.5: Structural Effects



Finally, figure 3.5 presents results of a decomposition of the structural effect. These results suggest that the overall shape of the structural effect is determined by the sector of employment and, to a certain extent, geography. These are the two characteristics that explain the negative values of the structural effect in some range in the lower end of the distribution. This negative contribution is mitigated to some extent by household demographics.

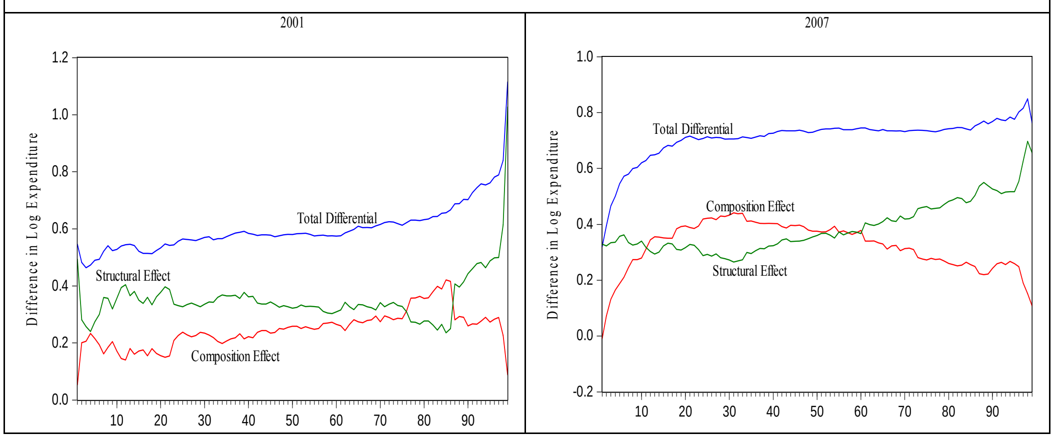
A Closer Look at the Rural-Urban Differential in Living Standards

Figure 3.6 Change in Rural-Urban Differential in Living Standards



Given the importance of urban bias in the pattern of economic growth in Cameroon, we take a closer look at how the rural-urban differential has changed over time and across quantiles. We also apply the generalized Oaxaca-Blinder decomposition to this differential both in 2001 and 2007 to try to identify some key factors that might explain the observed differences between the rural and the urban sector. Figure 3.6 shows a comparison of the rural-urban differential for 2001 and 2007. The fact that the curve for 2007 dominates that for 2001 confirms the finding in section 2 of this paper that the gap between the rural and urban sector has been growing over time. This dominance results also reveals that the gap has been widening across all quantiles. In both years the total differential generally increases across quantiles, implying that dispersion increases at all points of the distribution. However, in 2001 the increase is steeper at the top end of the distribution, while in 2007 it is steeper at the low end. This observation implies that, in 2001 urban residence increased inequality more at the top of the distribution compared to the bottom. The opposite happened in 2007.

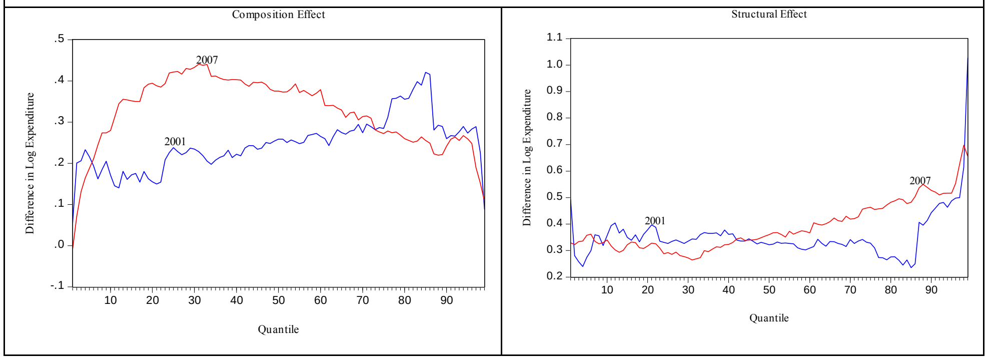
Figure 3.7 A Decomposition of the Rural-Urban Differential



To further explore what may lie behind this configuration of urban bias in Cameroon, we use the same decomposition technique that we applied to the growth incidence curve above. Figure 3.7 shows the results for both years under consideration. Focusing first on 2001, we notice that overall, the curve depicting the structural effect tends to follow a U-pattern while that representing the composition effect has, more or less, an inverted U-shape. Furthermore the structural effect dominates the composition effect over the whole range of the distribution, except between the 76th and the 88th

quantiles. This clearly shows that the greater increase in inequality at the top of the distribution in 2001 is due to the structural effect. The composition effect is pulling in the opposite direction.

Figure 3.8 Changes in Composition and Structural Effects over Time



In 2007 the inverted U-shape of the composition effect is more pronounced than in 2001. The curve representing the structural effect has more or less the same shape as in 2001. It tends to fall until the 31st quantile then increases monotonically afterwards. The composition effect dominates the structural effect between the 11th quantile and the median. Both curves are very similar between the median and the 60th quantile. Past that point the structural effect clearly dominates the composition effect. Considering the overall profile of the total rural-urban differential, we note that the effect of urban residence on inequality is mostly driven by the composition effect at the low end of the distribution and by the structural effect (with some dampening by the composition effect) at the top end of the distribution.

Finally, figure 3.8 shows how each of these two components evolved between 2001 and 2007. The composition effect increased significantly across quantiles up to about the 73rd quantile. In addition, its slope became steeper and peaked earlier (at the 33rd percentile compared to the 85th in 2001). This implies that the inequality enhancing effect associated with composition has become more concentrated at the lower end of the distribution in 2007 compared to 2001. There is a similar shift in the profile of the structural effect. While the curve has more or less a U-shape in both years, it bottoms out around the 30th percentile in 2007 and increases monotonically thereafter up to the 98th percentile. In 2001 the structural effect bottoms out around the 85th percentile and increases steeply afterwards. The key point that emerges from these observations is that composition contributes proportionately more to the increase in the rural-urban gap at lower quantiles while structure accounts for more of this increase at higher quantiles. In other words differences in household characteristics matter more for the poorest households (particularly in 2007) than returns to those characteristics. The reverse is true for better-off households. This finding suggests that prevailing social arrangements treat the people at the bottom of the distribution alike whether they live in urban areas or not. At the top of the distribution social arrangements in urban areas reward better the set of characteristics than arrangements in the rural areas [33].

4. Concluding Remarks

The Government of Cameroon has declared poverty reduction through strong and sustainable economic growth the central objective of its development policy. This paper therefore seeks to characterize the pattern of economic growth in Cameroon focusing on factors that might account for the observed heterogeneity in growth incidence. Our analysis of available data shows poverty fell by about 13 percentage points between 1996 and 2001. But, between 2001 and 2007, growth weakened significantly due to the fact that it was driven by low productivity sectors in the informal segment of the economy. Poverty incidence fell only by 1 percentage point over that period, and the Gini coefficient decreased by about 1.5 percentage point.

These aggregate changes in growth, inequality and poverty between 2001 and 2007 hide a great deal of heterogeneity in growth incidence in that period. A decomposition of changes in poverty outcomes over time shows that the pure growth effect dominates the inequality effect, except for the sub-period 2001-2007. Furthermore, the meager reduction in poverty observed in 2001-2007 is mostly due to a modest reduction in inequality. An application of the same methodology to deviations of

[33] Nguyen et al. (2007) find a similar pattern for the case of Vietnam using a quantile regression decomposition method proposed by Machado and Mata (2005). They explain their results by noting that, in accounting for rural-urban gap in well-being, one should not expect the structural effect to be important at the bottom of the distribution because poor people tend to work in jobs that pay little above the subsistence level. However, at the very top of the distribution, urban markets pay more for the same bundle of attributes than rural markets. One can therefore expect the structural effect to be more important than the composition effect in the upper end of the distribution. This explanation is also relevant to our case.

regional poverty from the national level reveals significant variation in the poverty impact of economic growth. Four regions out of 12 experienced significant increases in poverty between 2001 and 2007 while overall poverty tended to decline. We also find that, except for three regions, the real income effect dominates the inequality effect in explaining the divergence between regional and national poverty.

We use RIF regressions to link the growth incidence curve for the 2001-2007 period to household characteristics and perform counterfactual decomposition and thus account for heterogeneity of impact across quantiles. We find that the level of the GIC is explained by the composition effect while its shape is driven by the structural effect. The fact that the structural effect is negative or very close to zero on a wide segment of the distribution reveals that the weak performance of the economy over the period under consideration was mainly driven by the effect of the returns to household endowments. This supports the view that growth did not occur in high productivity sectors of the formal economy nor in the smallholder agriculture which employed 70 percent of rural heads of household in 2001 and 74 percent in 2007. Indeed, our RIF regression results show that returns to employment in smallholder agriculture were mostly negative in both years. Yet agriculture once was the main engine of growth in Cameroon even though its contribution to poverty reduction is debatable. The relationship between the composition effect and the structural effect over the whole distribution indicates that the observed gains at the lower part of the distribution are due to the structural effect while gains beyond the 10^{th} quantile are due mainly to the composition effect.

A further decomposition of the composition and structural effects reveals that the level and the dispersion of the full composition effect are accounted for by household demographics. Furthermore the contribution of assets to the composition effect is mostly driven by changes in the distribution of years of schooling. A similar decomposition of the structural effect shows that the overall profile of this effect is shaped by the sector of employment and, to a certain extent, by geography. These are the two dimensions that explain the negative values of the structural effect over some range of the lower end of the distribution.

One finding that stands out above all else is that *urban bias* and *regional disparity* are significant and have been increasing over time. A RIF regression decomposition of the urban-rural differential shows that it has been increasing over time across all quantiles. In 2001, the structural effect almost dominates the composition effect and thus accounts for both the level and shape of the total differential. The increase in inequality observed along the entire distribution in 2001 is thus due to the structural effect. In 2007, the configuration of the composition and structural effects shows that the former increases inequality at the lower end of the distribution while the latter does so in the upper end.

What is the policymaker to make of these findings? Fundamentally, the living standard achieved by an individual is an outcome of the interaction between opportunities offered by society and the readiness and ability of the individual to identify and exploit such opportunities. The perspective of development as opportunity equalization promotes a level playing field where individuals have equal opportunities to pursue freely chosen life plans and to be spared from extreme deprivation in outcomes. Our findings suggest that the pattern of growth in Cameroon is characterized by urban bias, regional disparity and a decline of the agricultural sector. This is hardly an outcome of opportunity-equalizing growth, and makes one question the effectiveness of the underlying development strategy. There is therefore a need to re-examine (and possibly reform) the mechanisms governing the allocation of public resources (e.g. investment in infrastructure, health and education) designed to support individuals' efforts to improve their standard of living, both in the rural and the urban sectors.

Appendix A: Poverty and Inequality by Region

Table A1 Regional Distribution of Poverty in 2001

	Headcount	Poverty Gap	Squared Poverty Gap	Watts	Population Share
Douala	10.89	2.07	0.72	2.61	9.70
Yaoundé	13.34	2.66	0.86	3.27	8.72
Adamaoua	48.38	15.39	6.38	20.31	4.47
Center	48.18	14.97	6.63	21.05	7.85
East	43.98	15.37	6.75	20.85	4.81
Far North	56.29	18.84	8.18	25.34	17.74
Coast	35.48	10.09	4.17	13.43	4.88
North	50.08	15.50	6.36	20.43	7.26
North West	52.48	20.90	10.70	30.83	11.52
West	40.33	11.10	4.19	14.19	12.06
South	31.55	7.35	2.43	9.04	3.45
South West	33.83	10.50	4.51	14.13	7.53
Cameroon	40.18	12.79	5.55	17.38	100.00

Source: Authors' Calculations

Table A2 Regional Distribution of Poverty in 2007

	Headcount	Poverty Gap	Squared Poverty Gap	Watts	Population Share
Douala	5.50	0.87	0.21	1.01	9.96
Yaoundé	5.94	0.97	0.24	1.13	9.60
Adamaoua	52.95	14.49	5.41	18.46	5.18
Center	41.19	9.48	3.10	11.68	7.63
East	50.40	15.69	6.22	20.25	4.66
Far North	65.87	24.58	11.21	33.35	18.11
Coast	31.08	7.65	2.71	9.60	3.50
North	63.66	20.99	8.58	27.43	9.85
North West	51.00	16.61	6.83	21.78	10.14
West	28.95	6.64	2.27	8.24	10.58
South	29.25	7.37	2.65	9.31	3.24
South West	27.51	6.87	2.47	8.65	7.55
Cameroon	39.90	12.31	5.03	16.11	100.00

Source: Authors' Calculations

Table A3 Regional Inequality in the Distribution of Welfare, 2001

	Gini	Atkinson-1	Atkinson-2	Mean Log Deviation	Theil
Douala	42.46	26.16	39.33	30.33	41.17
Yaoundé	42.59	26.00	39.88	30.11	37.79
Adamaoua	33.82	16.87	28.81	18.48	20.14
Center	34.62	18.55	34.61	20.52	22.06
East	34.21	17.66	31.33	19.43	20.26
Far North	32.97	16.05	27.77	17.49	18.69
Coast	34.19	17.62	31.36	19.39	20.24
North	36.16	19.23	31.11	21.36	25.62
North West	40.55	24.40	41.68	27.98	29.96
West	31.21	14.69	25.49	15.89	17.61
South	29.76	13.27	23.19	14.24	15.45
South West	38.02	21.41	35.88	24.09	26.81
Cameroon	40.41	24.00	38.82	27.45	33.75

Source: Authors' Calculations

TableA4 Regional Inequality in the Distribution of Welfare, 2007

	Gini	Atkinson-1	Atkinson-2	Mean Log Deviation	Theil
Douala	33.87	17.07	28.37	18.72	21.72
Yaoundé	33.15	16.60	28.02	18.15	21.07
Adamaoua	33.75	16.70	27.25	18.27	21.20
Center	28.07	11.91	20.72	12.68	14.13
East	32.88	15.79	26.63	17.19	18.99
Far North	36.52	19.14	30.28	21.24	25.07
Coast	31.86	15.33	25.71	16.64	19.26
North	35.33	18.22	28.57	20.12	24.65
North West	38.24	20.98	33.32	23.54	27.66
West	29.73	13.39	23.41	14.37	15.80
South	34.58	18.02	29.79	19.87	23.61
South West	33.24	16.54	28.67	18.08	19.69
Cameroon	38.96	21.94	35.82	24.77	27.88

Source: Authors' Calculations

Table A5 Shapley Decomposition of Urban- Rural Differences in 1996

		Difference	Scale	Inequality
	Headcount	-11.87	-16.12	4.26
	Poverty Gap	-4.43	-8.51	4.09
Urban	Squared Poverty Gap	-2.09	-4.96	2.87
	Watts	-6.12	-13.24	7.12
	Headcount	6.36	13.12	-6.76
	Poverty Gap	2.37	6.91	-4.53
Rural	Squared Poverty Gap	1.12	4.10	-2.98
	Watts	3.28	10.80	-7.52

Source: Authors' Calculations

Table A6 Shapley Decomposition Urban- Rural Differences in Poverty in 2001

		Difference	Scale	Inequality
	Headcount	-22.30	-22.25	-0.05
	Poverty Gap	-8.51	-8.20	-0.31
Urban	Squared Poverty Gap	-3.96	-3.80	-0.16
	Watts	-11.90	-11.39	-0.50
	Headcount	11.90	19.87	-7.97
	Poverty Gap	4.54	9.40	-4.86
Rural	Squared Poverty Gap	2.11	5.03	-2.91
	Watts	6.35	13.94	-7.59

Source: Authors' Calculations

Table A7 Shapley Decomposition Urban- Rural Differences in Poverty in 2007

		Difference	Scale	Inequality
	Headcount	-27.73	-22.05	-5.68
	Poverty Gap	-9.50	-7.69	-1.81
Urban	Squared Poverty Gap	-4.06	-3.44	-0.62
	Watts	-12.60	-10.42	-2.18
	Headcount	15.14	21.41	-6.27
	Poverty Gap	5.19	10.47	-5.28
Rural	Squared Poverty Gap	2.22	5.64	-3.42
	Watts	6.88	15.34	-8.46

Source: Authors' Calculations

Appendix B: Returns to Household Characteristics

Table B1: OLS and Unconditional Quantile Regression Coefficients on Log Expenditure, 2001

Eq Name:	OLS	Quantile 10	Quantile 25	Quantile 50	Quantile 75	Quantile 90
Dep. Var:	LPCEXP	RIFQT_10	RIFQT_25	RIFQT_50	RIFQT_75	RIFQT_90
Constant	13.159472	12.210145	12.571805	12.924253	13.729915	13.827996
	(0.0639)**	(0.1606)**	(0.1110)**	(0.0797)**	(0.0861)**	(0.1278)**
Male	-0.174076	-0.059530	-0.191985	-0.206050	-0.269449	-0.170897
	(0.0150)**	(0.0377)	(0.0261)**	(0.0187)**	(0.0202)**	(0.0300)**
Age of Head	-0.011417	0.006544	-0.005325	-0.007807	-0.013364	-0.009057
	(0.0022)**	(0.0055)	(0.0038)	(0.0027)**	(0.0030)**	(0.0044)*
Age Head Squared	0.000087	-0.000110	0.000011	0.000061	0.000117	0.000104
	(0.0000)**	(0.0001)*	(0.0000)	(0.0000)*	(0.0000)**	(0.0000)*
Age<5 (% of Household)	-0.007902	-0.007698	-0.009874	-0.006203	-0.008073	-0.010204
	(0.0005)**	(0.0012)**	(0.0008)**	(0.0006)**	(0.0006)**	(0.0009)**
Age 5 to <10 (%HH)	-0.012690	-0.015400	-0.014570	-0.010822	-0.013067	-0.013608
	(0.0004)**	(0.0011)**	(0.0008)**	(0.0006)**	(0.0006)**	(0.0009)**
Age 10 to < 15 (%HH)	-0.009995	-0.008390	-0.012397	-0.010170	-0.011347	-0.011913
	(0.0005)**	(0.0012)**	(0.0008)**	(0.0006)**	(0.0006)**	(0.0010)**
Age 15 to <20 (%HH)	-0.008513	-0.006559	-0.010314	-0.007059	-0.008955	-0.009859
	(0.0005)**	(0.0012)**	(0.0008)**	(0.0006)**	(0.0006)**	(0.0009)**
Age 20 to <25 (%HH)	-0.006930	-0.007858	-0.008141	-0.005454	-0.006481	-0.007318
	(0.0005)**	(0.0013)**	(0.0009)**	(0.0006)**	(0.0007)**	(0.0010)**
Schooling (Years)	0.035724	0.023833	0.036002	0.036836	0.036160	0.048525
	(0.0015)**	(0.0039)**	(0.0027)**	(0.0019)**	(0.0021)**	(0.0031)**
Land	0.000040	-0.000327	0.000266	-0.000542	0.000681	0.002758
	(0.0002)	(0.0005)	(0.0003)	(0.0002)*	(0.0002)**	(0.0004)**
Access to Credit	0.272581	0.344990	0.502057	0.167755	0.174148	0.203044
	(0.0187)**	(0.0469)**	(0.0324)**	(0.0233)**	(0.0251)**	(0.0373)**
Has Migrant (s)	-0.003390	-0.093183	0.035803	-0.008674	-0.007870	-0.013549
	(0.0110)	(0.0277)**	(0.0191)	(0.0137)	(0.0148)	(0.0220)
Distance to Nearest Hospital	-0.007699	-0.018778	-0.005528	-0.003056	-0.001005	-0.000380
	(0.0010)**	(0.0024)**	(0.0017)**	(0.0012)*	(0.0013)	(0.0019)
Distance to Nearest Tarred Road	0.000842	0.003488	-0.000158	0.001588	0.000488	0.000673
	(0.0002)**	(0.0004)**	(0.0003)	(0.0002)**	(0.0002)*	(0.0003)
Public Sector	0.137185	-0.261937	0.280543	0.158812	0.164989	0.327043
	(0.0247)**	(0.0619)**	(0.0428)**	(0.0307)**	(0.0332)**	(0.0493)**
Private Sector (Formal)	0.268188	-0.061321	0.392699	0.266786	0.271007	0.346203

	(0.0249)**	(0.0626)	(0.0433)**	(0.0311)**	(0.0336)**	(0.0498)**
Agriculture	-0.046850	-0.240546	0.204856	-0.078711	-0.125636	-0.046576
	(0.0183)*	(0.0459)**	(0.0317)**	(0.0228)**	(0.0246)**	(0.0365)
Non-Agriculture Informal	-0.003375	-0.098520	0.169686	-0.053357	-0.062985	-0.025741
	(0.0200)	(0.0503)	(0.0348)**	(0.0250)*	(0.0270)*	(0.0400)
Unemployed	0.074510	-0.096578	0.368856	0.163483	0.251011	-0.256259
	(0.0365)*	(0.0915)	(0.0633)**	(0.0454)**	(0.0491)**	(0.0728)**
Urban	0.358252	0.327079	0.411417	0.424686	0.326439	0.367371
	(0.0173)**	(0.0434)**	(0.0300)**	(0.0215)**	(0.0233)**	(0.0345)**
Adamaoua	0.070304	0.056012	-0.011889	0.119813	0.035959	0.011751
	(0.0321)*	(0.0806)	(0.0557)	(0.0400)**	(0.0432)	(0.0642)
East	-0.020939	-0.209054	-0.159996	-0.025619	-0.010703	-0.038472
	(0.0264)	(0.0663)**	(0.0459)**	(0.0329)	(0.0356)	(0.0528)
Far-North	0.122657	0.072381	0.034542	0.153209	0.141260	0.151345
	(0.0197)**	(0.0494)	(0.0342)	(0.0245)**	(0.0265)**	(0.0393)**
Coast	0.110042	0.052038	0.033475	0.104869	0.143391	0.102709
	(0.0226)**	(0.0569)	(0.0393)	(0.0282)**	(0.0305)**	(0.0453)*
North	0.171011	0.148245	0.012795	0.116118	0.155918	0.255212
	(0.0241)**	(0.0606)*	(0.0419)	(0.0301)**	(0.0325)**	(0.0482)**
North-West	-0.097031	-0.273372	-0.206432	-0.040859	-0.032324	-0.018093
	(0.0202)**	(0.0507)**	(0.0351)**	(0.0252)	(0.0272)	(0.0403)
West	0.095338	0.421776	0.038442	0.088763	0.011295	-0.047624
	(0.0193)**	(0.0485)**	(0.0336)	(0.0241)**	(0.0260)	(0.0386)
South	0.118213	0.391487	0.347940	0.290900	-0.165893	-0.140165
	(0.0359)**	(0.0901)**	(0.0623)**	(0.0447)**	(0.0483)**	(0.0717)
South-West	0.040321	0.027439	0.043129	0.149609	-0.123667	-0.124648
	(0.0222)	(0.0558)	(0.0386)	(0.0277)**	(0.0299)**	(0.0445)**
Observations:	11000	11000	11000	11000	11000	11000
R-squared:	0.3659	0.0970	0.1992	0.2909	0.2555	0.1558
F-statistic:	218.3177	40.6275	94.0738	155.1603	129.8469	69.7986

Source: Authors' Calculations (Standard Errors in Parentheses)

Table B2: OLS and Unconditional Quantile Regression Coefficients on Log Expenditure, 2007

Eq Name:	OLS	Quantile 10	Quantile 25	Quantile 50	Quantile 75	Quantile 90
Dep. Var:	LPCEXP	RIFQT_10	RIFQT_25	RIFQT_50	RIFQT_75	RIFQT_90
Constant	13.304263	12.197708	13.120938	13.238181	13.718763	13.899547
	(0.0629)**	(0.1408)**	(0.1113)**	(0.0882)**	(0.1018)**	(0.1419)**
Male	0.070325	-0.154760	-0.224476	0.071366	0.401929	0.244113
	(0.0367)	(0.0822)	(0.0650)**	(0.0515)	(0.0595)**	(0.0829)**
Age of Head	-0.013158	-0.008564	-0.016820	-0.010976	-0.014366	-0.005371
	(0.0018)**	(0.0041)*	(0.0033)**	(0.0026)**	(0.0030)**	(0.0041)
Age Head Squared	0.000114	0.000121	0.000139	0.000089	0.000095	0.000041
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)
Age<5 (% of Household)	-0.005484	0.000316	-0.005747	-0.005578	-0.007783	-0.010410
	(0.0004)**	(0.0009)	(0.0007)**	(0.0005)**	(0.0006)**	(0.0009)**
Age 5 to <10 (%HH)	-0.007811	-0.003733	-0.007685	-0.007811	-0.011619	-0.011752
	(0.0004)**	(0.0009)**	(0.0007)**	(0.0006)**	(0.0007)**	(0.0009)**
Age 10 to < 15 (%HH)	-0.008318	-0.011155	-0.009006	-0.007767	-0.007190	-0.008996
	(0.0004)**	(0.0009)**	(0.0007)**	(0.0006)**	(0.0007)**	(0.0009)**
Age 15 to <20 (%HH)	-0.007076	-0.005308	-0.006029	-0.006312	-0.009886	-0.010217
	(0.0004)**	(0.0009)**	(0.0007)**	(0.0005)**	(0.0006)**	(0.0009)**
Age 20 to <25 (%HH)	-0.001457	0.000448	-0.000346	-0.000942	-0.002167	-0.002464
	(0.0004)**	(0.0009)	(0.0007)	(0.0006)	(0.0007)**	(0.0010)**
Schooling (Years)	0.027913	0.022405	0.020552	0.027924	0.031056	0.038209
	(0.0014)**	(0.0031)**	(0.0025)**	(0.0020)**	(0.0023)**	(0.0032)**
Land	0.000909	0.001197	0.001421	0.000104	0.000284	0.002935
	(0.0003)**	(0.0006)	(0.0005)**	(0.0004)	(0.0005)	(0.0006)**
Access to Credit	0.121824	0.326021	-0.003454	0.153329	0.183045	0.187816
	(0.0164)**	(0.0367)**	(0.0290)	(0.0230)**	(0.0265)**	(0.0370)**
Has Migrant (s)	0.007313	0.059992	-0.047730	-0.027361	0.053349	0.025172
	(0.0092)	(0.0206)**	(0.0163)**	(0.0129)*	(0.0149)**	(0.0208)
Distance to Nearest Hospital	-0.001734	0.003170	-0.003044	-0.002540	0.000407	-0.001568
	(0.0005)**	(0.0011)**	(0.0009)**	(0.0007)**	(0.0008)	(0.0011)
Distance to Nearest Tarred Road	0.000625	0.001278	0.001463	0.000091	0.000473	-0.000360
	(0.0001)**	(0.0003)**	(0.0002)**	(0.0002)	(0.0002)*	(0.0003)
Public Sector	0.101134	0.145912	0.018378	-0.033898	0.294486	0.314242
	(0.0396)*	(0.0886)	(0.0700)	(0.0555)	(0.0641)**	(0.0893)**
Private Sector Formal	0.011229	0.121331	0.017644	-0.156668	0.013729	0.243870
	(0.0404)	(0.0905)	(0.0716)	(0.0567)**	(0.0655)	(0.0913)**
Agriculture	-0.253115	-0.142792	-0.362748	-0.348374	-0.149680	-0.090588
	(0.0358)**	(0.0801)	(0.0633)**	(0.0502)**	(0.0579)**	(0.0808)
Non-Agriculture	-0.144915	0.126827	-0.050514	-0.181781	-0.160270	-0.221364

Informal						
	(0.0350)**	(0.0783)	(0.0619)	(0.0490)**	(0.0566)**	(0.0789)**
Unemployed	-0.190645	-0.026608	-0.141813	-0.232494	-0.135369	-0.072094
	(0.0403)**	(0.0903)	(0.0714)*	(0.0566)**	(0.0653)*	(0.0911)
Urban	0.428321	0.075966	0.304728	0.548580	0.683162	0.563511
	(0.0162)**	(0.0362)*	(0.0286)**	(0.0227)**	(0.0262)**	(0.0365)**
Adamaoua	0.011547	-0.053626	0.002316	-0.066617	0.082621	0.123803
	(0.0233)	(0.0521)	(0.0412)	(0.0327)*	(0.0377)*	(0.0526)*
East	-0.158765	-0.413217	-0.303400	-0.148873	-0.105910	-0.029665
	(0.0240)**	(0.0537)**	(0.0424)**	(0.0336)**	(0.0388)**	(0.0541)
Far-North	-0.176944	-0.743800	-0.448753	-0.088092	0.002126	0.115887
	(0.0170)**	(0.0381)**	(0.0301)**	(0.0239)**	(0.0275)	(0.0384)**
Coast	-0.013519	0.084526	0.149400	-0.024614	-0.250750	-0.208432
	(0.0338)	(0.0756)	(0.0597)*	(0.0473)	(0.0546)**	(0.0762)**
North	-0.137783	-0.232887	-0.397939	-0.157968	-0.000971	0.079831
	(0.0182)**	(0.0408)**	(0.0323)**	(0.0256)**	(0.0295)	(0.0412)
North-West	-0.112079	-0.402653	-0.311221	-0.095947	-0.022289	0.059885
	(0.0207)**	(0.0463)**	(0.0366)**	(0.0290)**	(0.0335)	(0.0467)
West	0.104418	0.079892	0.222665	0.153857	-0.000626	-0.078137
	(0.0200)**	(0.0447)	(0.0353)**	(0.0280)**	(0.0323)	(0.0451)
South	0.096130	0.032081	0.203152	0.174641	0.095795	-0.113482
	(0.0295)**	(0.0661)	(0.0522)**	(0.0414)**	(0.0478)*	(0.0666)
South-West	0.149720	0.147742	0.191804	0.264295	0.024753	0.043076
	(0.0203)**	(0.0454)**	(0.0359)**	(0.0284)**	(0.0328)	(0.0458)
Observations:	11388	11388	11388	11388	11388	11388
R-squared:	0.4994	0.1991	0.3137	0.3804	0.3316	0.1744
F-statistic:	390.7395	97.3824	179.0128	240.4643	194.2671	82.7593

Source: Authors' Calculations (Standard Errors in Parentheses)

Figure B1: Returns to Education and Access to Credit

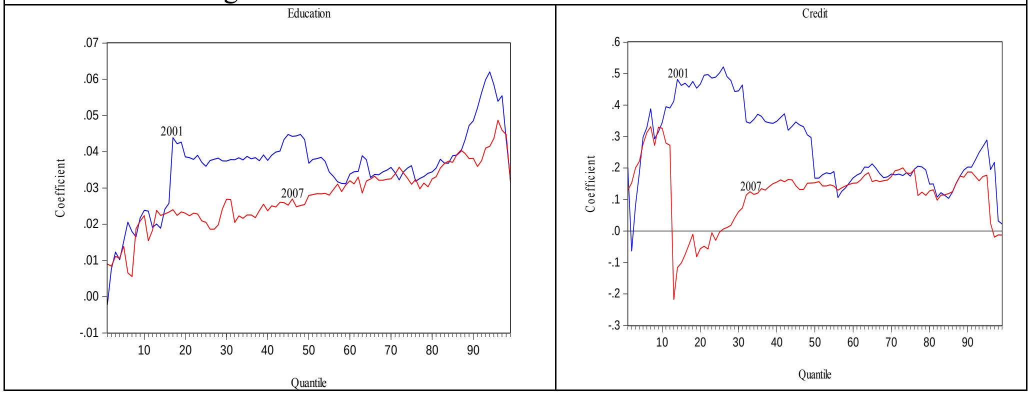


Figure B2: Returns to Land and Migration

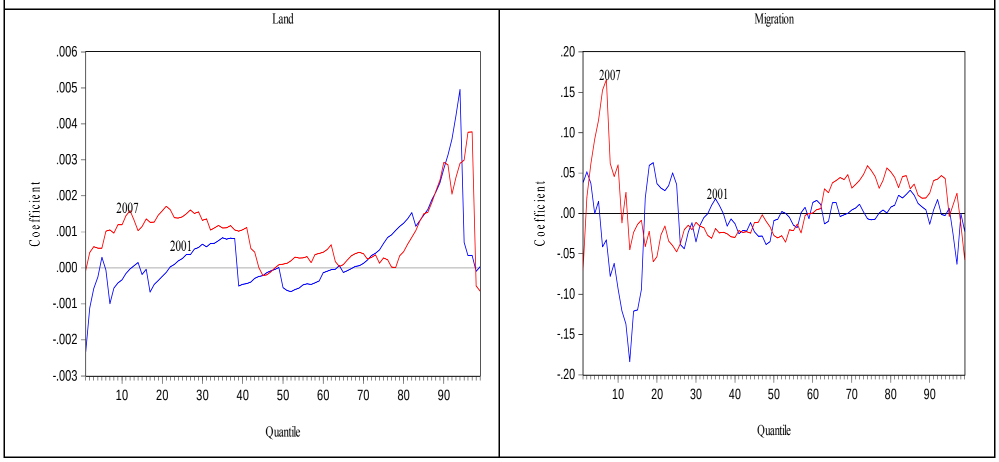


Figure B3: Returns to Formal Sector Employment

Figure B4: Private and Public Sectors Compared

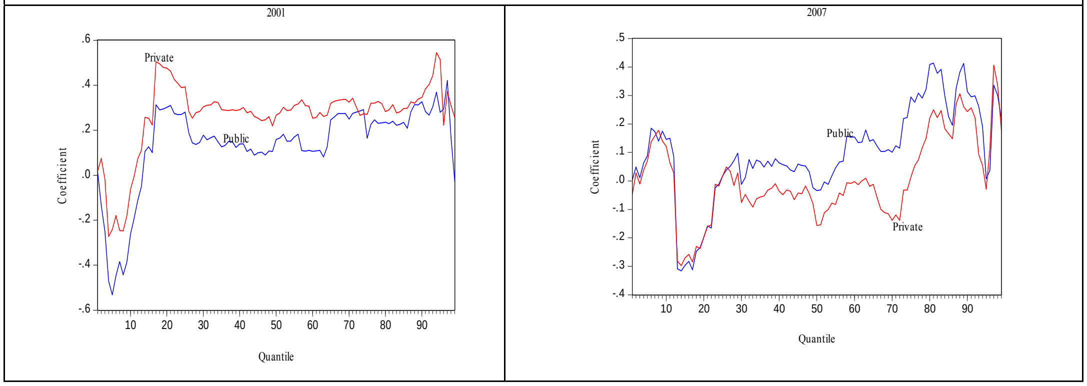
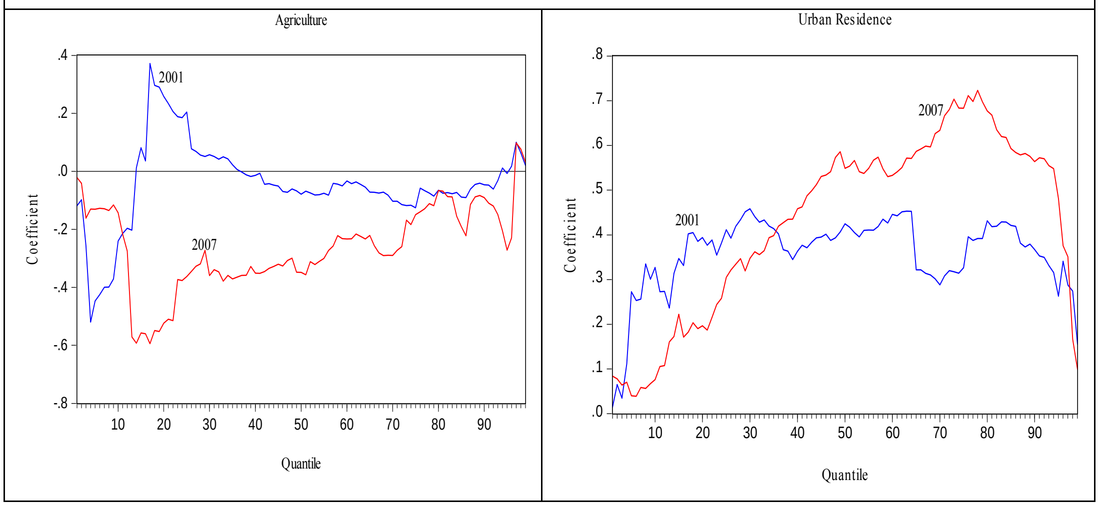


Figure B5: Returns to Smallholder Agriculture and Urban Residence



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